AFIT INSTITUTE OF TECHNOLOGY

A RESPONSE SURFACE APPROACH TO THE COMBAT RESCUE AND SPECIAL OPERATIONS SIMULATION MODEL

THESIS

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Captain USAF

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Presented to the Faculty of the School of Engineering

of the Air Force Institute of Technology

Air University

in Partial Fulfillment of the

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Captain USAF

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Preface

I would like to thank God and the following individuals for their support:

My advisor, Major Kenneth Bauer, for his patience, insight, and understanding of me personally and professionally.

My reader Lt Col Robinson, for his helpful editing, and sparking my interest in the classroom.

My daughter, Ashley, who will now get to play with me every day.

And most of all I thank my wife, Mahaley, for putting up with our extended vacation at AFIT.

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Abstract

This thesis proposes a methodology for producing response surface metamodels to enhance the force sizing capability at Military Airlift Command. Output generated by the Combat Rescue and Special Operations Forces simulation model was used to develop the sets of predictive response equations. The methodology produced statistically good predictive metamodels using a Box and Behnken fractional factorial. Multivariate techniques were used to reduce the dimensionality of the responses modeled by the simulation model to further enhance the decision making process on force sizing issues. Keywords: [illegible] simulation, [illegible], Computer programs,

I. PROBLEM FORMULATION

Introduction

Currently Air Force special mission aircraft capability is measured using Headquarters Military Airlift Commands Combat Rescue And Special Operations Forces (CRASOF) simulation model. This model measures capability in terms of the number of successful rescue and special operations sorties successfully flown by assigned aircraft. The special missions used to determine a given force structure capability for any scenario are the airlift support provided for; infiltration, exfiltration and the resupply of special forces, combat rescue of downed aircrews, and refueling of special mission aircraft.

The analysis process used during force sizing exercises involves specifying types and numbers of aircraft and making several simulation runs using the CRASOF simulation model to determine the mission capability of each of the separate force sizes. On the basis of the simulation output and certain constraints e.g., budgetary constraints, the different force structures are rank ordered in terms of preference. This entails loading separate data files for each run, compiling the output into a usable format, and briefing results.

Research Problem

The CRASOF analysis process is very time consuming. Problems occur when computer processing time is not available, and questions on capability of proposed force sizes are not answered in an expeditious way.

Research Question

Given the output data generated by CRASOF, is there a method which when used in the force sizing analysis process expedites the analysis process?

Scope and Limitations

This research will demonstrate the utility of using response surface metamodels to enhance the force sizing analysis process at Hq MAC. The research conducted will use unclassified scenarios from the CRASOF simulation model to generate the required data.

The research conducted will not attempt to generate concrete solutions to various force sizing issues. The unclassified response surfaces resulting from this research will be used to demonstrate the utility of using response surface methodology in conjunction with CRASOF at Hq MAC.

Research Methodology

The second chapter is a literature review of current methods used for response surface derivations.

The third chapter provides an overview of how the simulation model CRASOF is structured. The variety of uses for CRASOF are then discussed and finally a summary of how the CRASOF simulation model has been validated.

Chapter four presents the response surface design and the methods used to verify the response surfaces adequacy. An explanation of the scenario data used and the set up of the experimental design is given also. Relevent factors are evaluated in detail using several of the methods expanded on in the literature review.

The fifth chapter goes into further analysis of the input factors and output factors combined and evaluated from a multivariate point of view. Factor Analysis methodology is used.

Chapter six consolidates the results of chapters four and five and presents individual results pertaining to the validity of the response surfaces generated in this research. In addition insights brought out by the multivariate analysis are presented.

Chapter seven summarizes the objectives of the research and the insights resulting from the research. Recommendations for the use of metamodels with CRASOF are made and recommendations for further study are presented.

II. Literature Review

Scope

The goal of this research is to demonstrate the utility of using a combined modeling approach for force sizing analysis. The combined modeling approach is the use of any analytic auxiliary model, metamodel, which is used to aid in the interpetation of a more detailed model (Freidman, 1988;p939).

Organization

This literature review includes a brief overview of what response surface methodology is. The discussion will cover some of the more current research in response surface methodology applied to simulation analysis. The next topic discussed will be the use of experimental design in metamodel building. An overview of different techniques available for the verification and validation of response surface models is then examined. The conclusion will tie together the aspects of the discussion applicable to this research.

Discussion

Experimental Design. Before a metamodel cam be computed, attention should be focused on the collection of data from the simulation model. Data is collected over several runs of the simulation by varying the values of inputs and then observing the corresponding responses. Experimental design is used to methodically change the value of inputs to gain as much insight as possible about the sensitivity of responses to input changes (Kleijnen 1987;259).

Key Terms. Two basic terms associated with the design of experiments are factor and level. The inputs to a simulation program are called factors in the experiment. Factors include parameters, variables, and behavioral relationships that can

change during or before the running of a simulation. Parameter changes in CRASOF can be associated with changing the theater of operation that is modeled. The variables for the purpose of this research are the types of aircraft used in each theater scenario. These inputs are also called independent factors. The simulation output used as the measure of capability, number of succesful missions, is the response or dependent factor. Behavioral relationship factors for CRASOF are the ways in which the aircraft prioritize the completion of the different mission types..

The values of a factor over the runs of a simulation are called the levels of the factor. The number of factor levels is important in determining the number of simulation runs required to extract information on response sensitivity. For an experimental design with number of levels, L, greater than or equal to 2 and number of factors, K, greater than or equal to 2, the number of runs is equal to L^K. The number of levels greater than or equal to 2 generates a readily apparent problem. The problem is "...the exponential growth in the number of runs as the number of factors K grows," (Kleijnen, 1987; 259). If the number of factors is small, then the number of runs required is manageable (Law and Kelton, 1982; 377). Once the number of factors K begins to grow the use of various techniques in design of experiments can reduce the number of runs.

Design Approaches. There are three distinguishable approaches to the design of experiments; one factor at a time, all factor level combinations, and specially selected combinations (Kleijnen, 1987; 260).

The one factor at a time approach involves holding all but one of the factors at a base value and the other factor is then varied at different levels. This strategy is repeated to examine each of the input factors one at a time. If the number of factors is greater than 2 this approach can be very inefficient (Law and

Kelton, 1982; 372).

The second approach is the full factorial or all factor level combination method. This method requires many more combinations than does the one factor at a time method. Two benefits result from the use of full factorials (Kleijnen, 1987; 269). As the number of runs increases, the variance, σ^2, decreases dramatically. This is not the case in the first approach where variance remains constant. The second benefit is the effectiveness in using a full factorial. The first approach results in only the estimation of the K + 1 factor effects. Using the full factorial, interaction effects are also estimated. Full factorials are excellent for use if the key factors are unknown and the research is attempting to find significant factor effects.

If certain interactions are known to be insignificant, then the incomplete or fractional factorial approach can be used. The fractional factorial has the same efficiency as the full factorial (Kleijnen, 1987; 270). A key point to remember when using fractional factorials is to use the correct design when estimating effects. Factor effects can be confounded or unseparable from other effects giving misleading results. To avoid this problem, fractional designs with specified resolution are used to insure no confounding of effects of interest. The resolution, R, of an experiment with p factors is the number of effect types not confounded with any other effects having R-p factors (Smith and Mauro, 1984; 255). An example would be a 2^{8-4} resolution 4 design where R equals 4, and p equals 8. Any effect with 8 minus 4 factors will not be confounded with any other effect with less than 4 factors.

<u>Design Planning</u>. When designing a simulation experiment the assumptions made prior to initial simulation runs are crucial

to the experimental design (Steinberg and Hunter, 1984; 77). It is important to evaluate the sensitivity of the experimental design to the assumptions made prior to design creation. The term used to describe this sensitivity is robustness. Assumptions in experimental design are necessary when uncertainty exists as to the structure of the true response model. Steinberg and Hunter (1984) suggest three types of designs that can provide insight into model building when no clues exist concerning the structure of the model.

The first design is a model-robust design. Box and Draper (1959) state that model-robust designs focus on minimum average mean square error as it relates to the bias of a proposed model. The minimum biased design tends to make the analysis robust or insensitive to inaccuracies in the proposed response model (Steinberg and Hunter, 1984; 77).

When considering the error term of the response model, the assumption is that the error term is independent and identically distributed (Draper and Smith, 1981; 23). Error-robust designs deal with misjudgement in the assumptions about the error distribution. Box and Draper (1975) suggest ways in which robustness to error assumptions can be made.

If the assumptions made are reasonably valid and the goal is to search through models until an acceptable model is found, then model-sensitive or non-robust designs are required. The search for an appropriate model is done by "... highlighting the uncertainties and inaccuracies in order to modify or refine the proposed model," (Steinberg and Hunter, 1984; 78). The key assumption made in this research is that a proposed experimental design matrix with responses can be adequately described as

$$\text{response} = \text{model} + \text{error}.$$

Model-sensitive designs are appropriate when searching for the best predictive model. The ability to produce sensitivity in

response variables through changes in input factor levels is a key component of response surface analysis (Kleijnen, 1987; 261).

Response Surface Methodology. Response surface methodology or regression analysis, is a statistical tool which uses the interaction between two or more quantitative variables, so that one variable can be predicted based on the value of the other(s) (Neter, 1974;p21). There are two concepts that are basic to response models:

(1) A tendency for the dependent variable, Y, to vary with the independent variable(s), X_i, in a statistical way,

(2) A scattering of observed values of Y around the curve of statistical relationship (Neter, 1974;p21).

The relationship between the dependent and independent variables is denoted by,

$$Y = B_o + B_i X + \varepsilon_i \qquad (1.1)$$

where, Y is the dependent variable of interest

X is the set of known constant values of the independent variables

B_o and B_i is the set of parameters

ε_i is the true error or deviation in the regression model

(ε_i is assumed to be independent, normal random variables, with mean equal to zero and constant variance σ^2)

(Box and Draper, 1981; 9).

Given that the data is readily available, through simulation, the only unknowns are the B_o, B_i, and ε_i. A good way to determine estimates b_i's of the B_i's is to use the method of least squares (Draper, 1981;p8). The method of least squares evaluates the deviation of Y from its expected value, E(Y),

$$Y - (B_o + B_i X) = \hat{\varepsilon}_i \quad \text{for, } i = 1 \ldots n \qquad (1.2)$$

Taking the sums of the squared deviations from the true model,

$$S = \Sigma(\hat{\varepsilon}_i^{\,2}). \qquad (1.3)$$

The best values for b_o and b_i are those values which minimizes the value of S, the sum of the squared deviations. Once the estimators $b=(b_o, b_1, ..., b_n)$ have been computed, the regression equation

$$E(Y) = Y = B_o + B_i X \qquad (1.5)$$

can be estimated by the parameters b in the least squares regression equation,

$$\hat{Y} = b_o + b_i x_i . \qquad (1.5)$$

$\hat{Y}$ is denoted as the fitted or predicted value of the independent variable Y_i based on the estimators $b_o$and b_i for a given set of x_i. The response equation, 1.5, is then evaluated in several ways to determine its accuracy and applicability for its derived use (Draper and Smith, 1981; 17).

Applications. Response surface methodology has been used in a number of studies in recent years covering a broad spectrum of topics including manpower issues and force structure procurement issues. Several specific topics are covered here to give an idea of the capability of response surface methodology to enhance the analysis process when correctly applied.

Kraus (1986), in a thesis that upgraded the capability of CRASOF to handled more realistic scenarios, used response surface analysis in his analysis of the new simulation model. Three basing options were studied on the basis of analysis of eight response variables. How well each basing option met the mission priorities was the measure of effectiveness. The goal was to find a maximizing function of basing locations for each of the three theater scenarios modeled.

McKoy (1988), used response surface methodology to help develop goals for a goal programming problem that dealt with manning issues for helicopter pilots. Response surface methodology produced equations from simulation data that were interpeted as policy variables. The policy variables were later

used in a goal programming optimization program.

Percich (1987), applied response surface methodology to a manpower issue that dealt with strategic airlift pilots. Percich developed two response surfaces. Then using techniques described later in this research he was able to produce an analytic submodel that replicated the results produced by the simulation model which produced the original data. Further reading on other than military uses of response surface methodology can be found in Draper (1981; 691-692).

Verification. When response surface methodology is applied to simulation output data to produce a metamodel, a model of the output from another model (Freidman and Pressman, 1988; 939), close attention must be paid to the validity and adequacy of the metamodel. A key point to remember when dealing with metamodels is "the metamodel supplements, not replaces, the decision model by simplifying the sensitivity calculations "(Blanning, 1974: 37). Since the objective of this research is demonstrating the utility of response surface metamodels applied to CRASOF, the following review covers aspects of checking the adequacy and validity of metamodels as predictors of simulation models.

Metamodel adequacy checking or model verification involves checking for lack of fit, residual analysis, and the determination of independent factors that influence the response (Montgomery and Peck, 1982; 42).

Lack of fit in a response equations is a significantly different value for the residual mean square error compared to a prior estimate of the true varince. A key component of lack of fit testing is to remember that the best fit does not always imply the best predictor. For example a metamodel may have been developed primarily for predicting new observations for a particular system, however, factors that were not known during metamodel building could play a significant role in the predicted

response. This could cause predictions of the misspecified model to be inaccurate and useless (Montgomery and Peck, 1982; 424). A lack of fit test can only be conducted if there are repeat observations made for a given input level or design point. When designing your experiment and you have available exact repeats the following four steps as outlined can be used for lack of fit testing (Draper and Smith, 1981; 40).

1. Fit the model, compute the usual anova table with regression and residual entries. Do not perform a F-test for overall regression yet.

2. Separate out the pure error and lack of fit sums of squares from the residuals. If no pure error check via residual plots instead.

3. Perform the F-test for lack of fit. If significant lack of fit is exhibited, go to 4a. If the lack of fit test is not significant, so that there is no reason to doubt the adequacy of the model go to 4b.

4a. Significant lack of fit. Stop the analysis of the model and seek ways to improve the model by examining residuals. At this point transformation and/or the addition of higher order terms may be needed Do not carry out the F-test for overall regression, do not attempt to obtain confidence intervals. The assumptions on which these calculations are made are not true if there is lack of fit in the model fitted.

4b. No significant lack of fit. Recombine the pure error and lack of fit sum of squares into the residual, use the residual mean square as an estimate of variance, V(y). Carry out F-test for overall regression, obtain confidence intervals for the true mean value of Y, evaluate R-square, and so on. Note the residuals should still be plotted and checked for peculiarities. (Draper and Smith, 1981; 40).

The next step in verification is residual checking. Residuals are defined as

$$e_i = Y_i - \hat{Y}_i \tag{1.6}$$

where $i=1,2,\ldots,n$ and Y_i is the response observed in your data and $\hat{Y}_i$ is the value generated by using the regression equation fitted to the input data. This difference e_i is the amount of information not explained by the regression equation. Examining residuals will result in either rejecting or not rejecting the assumptions made about the metamodel. Two plots of e_i can be made that are applicable to this research; e_i vs $\hat{Y}_i$, and the overall plot which can be constructed as a normal or half-normal plot. Examination of residuals and comparison with known tendencies of plots of incorrect regressions will lead to reexamination of the metamodel or continuing on with your analysis.

Independent factors is another method of determining the adequacy of the metamodel is to examine the independent factors from your data set to find the best subset of factors. One way of examining these factors is the the use of Mallows C_p statistic (Draper and Smith, 1981;p175). The complete equation for Mallows statistic is

$$C_p = RSS_p/s^2 - (n-p) \tag{1.7}$$

where n is the number of observations taken. The C_p statistic is compared with p and the closer the ratio of C_p to p is to one, the better the metamodel with p parameters is. Another method of discerning the utility of a metamodel with the C_p statistic is to plot the C_p statistic for several metamodels against the $E(C_p)=p$ line. This line can be used as a bench mark for tradeoffs in that the C_p statistic "... is an estimate of the overall sum of squares

of discrepencies, variance error plus bias error, of the fitted model from the true model" (Draper, 1981;p300). The tradeoff comes from being able to chose a biased metamodel that has a larger RSS_p where C_p is less than p, but an estimated variance error plus bias error smaller than the true models. Or a choice can be made for a metamodel with more parameters that fits better but has a larger variance error plus bias error than does the true model.

Another relevent method of independent factors analysis is stepwise regression in cunjunction with R^2 analysis. Stepwise regession is accomplished by inserting variables into the regression equation and checking the inserted variables correlation with the output response. The higher the correlation the better the chance of the variable staying in the equation. The variable input is regressed on by the output variable and a F-test is done to check the significance of the input variable. If the F-test is significant the variable stays in the response equation. The next input variable with the highest correlation to the response, taking into account the input variable already regressed, is added to the equation and the F-test is conducted again. Also a R^2 measure is taken which is the percentage of variation explained by the regression equation, R^2 is equal to the (sum of squares due to regression)/(total sums of squares, corrected for the mean) or

$$R^2 = \Sigma(\hat{y}_i - \bar{Y}) / \Sigma(y_i - \bar{Y}) \qquad (1.8)$$

This process continues until no other input variables can enter the regression equation and the process stops.

Validation. When the adequacy of the metamodel has been determined, the final process is determining the validity of the metamodel. A question that arises while checking metamodel validity is: "Are the conclusions drawn from this metamodel applicable only to the simulation model or, by extension, given the validity of the simulation model, may they be applied to the real-world system under study?" (Freidman, 1988;p940). One way to determine the answer to this question is to use new data and derive predicted responses using the metamodel, then compare these responses to those from the simulation model and make inferences about validity.

Here are two methods commonly used to validate models; analytical validation which is checking each part of the model, and synoptic validation which is insuring that an acceptable response is achieved for each of a set of inputs (Finlay and Forey, 1988; 935). Sargeant (1987) refers to synoptic validation as operational validation and discusses forms of operational validation. Some of the ways in which operational validation can take place are; (1) predictive validation where the model is used to forecast system behavior and comparisons are made to actual system behavior (simulation results), (2) face validity where people knowledgeable about the system under study determine whether the behavior is reasonable, (3) data splitting or historical data validation is setting aside some of the original data to build the metamodel and using the remaining observations to investigate the models predictive performance (Sargeant, 1987; 34). Any of the above methods can be used to accomplish validation. The best hedge against poor validation is the use of at least two of the validation approaches so that there is an overlapping of coverage in validation leading to the models acceptance. For the purposes of this research, the operational approach will be used. "Operational validity is primarily

concerned with determining that the model's output behavior has the accuracy required for for the model's intended use..." (Sargeant, 1987; 35). At least two sets of experimental data should be used in operational validation when comparing output from the metamodel and the system under study. Three basic approaches to comparison of the metamodel with the system model are;

(1) graphs of the system behavior versus the metamodel behavior,

(2) confidence intervals, and

(3) hypothesis tests.

Summary. Mckoy (1988) employs a methodology which is appropriate for use in handling the verfication portion of this research. The methodology he uses is taken from Bauer (1988) and is listed at figure 1.

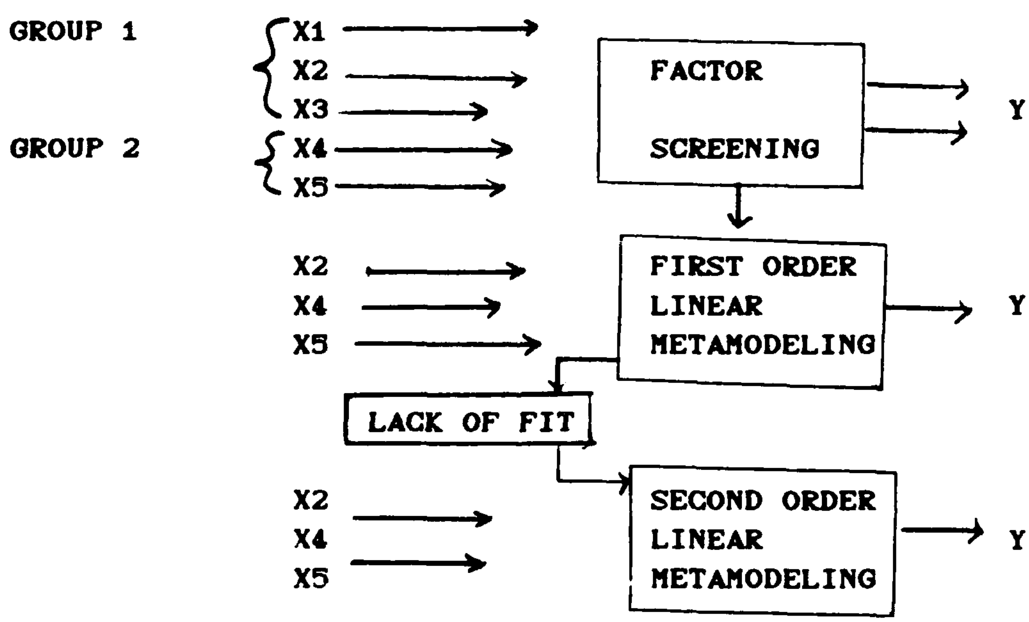

Figure 2-1 Meta Modeling Building

Bauer (1988)

This method incorporates using stepwise regression to accomplish screening of significant factors out of the input data. Because

simulation data is used for input data, replications can be generated by manipulating the random number seeds when running the simulation. The replications built into the model design can be used to conduct lack of fit tests. The stepwise regression program which is accomplished using the Statistical Analysis System (SAS), will also conduct lack of fit tests and compute R^2. SAS also computes residuals for performing the residual plots. Independent factors will also be analized using multivariate techniques discussed in chapter five. The validation phase will be accomplished using graphical and predictive analysis.

III. Current Implementation

Introduction

This chapter will provide a brief history of CRASOF and its previous uses. The discussion will expand on the structure and flow of the CRASOF simulation code, input data files and output data files.

Model Variations

The CRASOF simulation model was developed over a period from 1983 to 1984 under the direction of Hq MAC/XPS. The original simulation model was developed to study aircraft tanker refueling requirements for special mission aircraft. The model developers, while meticulous in their development of the air refueling logic, decided to make the simulation model flexible enough to answer other airlift questions (Kraus, 1986; 26).

After the models development and acceptance for use in performing the tanker force requirement study, the model was used to accomplish the Combat Rescue and Air Force Special Operations Force Minimum Risk Forces Study for Hq MAC/XP in 1985 and 1986. During this time period the model was coded using FORTRAN and Simulation for Alternative Modeling, SLAM. The CRASOF simulation model used at that time was set up to operate forces from one basing location at a time which lead to certain assumptions having to be made to account for the co-location of aircraft assets.

Kraus (1986) completed a thesis study that revised CRASOF to operate as a multi-basing type simulation. The new version more realistically represented the scenarios under study. This new version of CRASOF was used at Hq MAC/CAAG until 1987. With the ability to distribute aircraft within a given scenario, CRASOF was considered a more reliable or valid simulation model. However, with the development of the multi-basing mode, the run time for

CRASOF increased dramatically which slowed down the analysis process of providing accurate yet timely information to decision makers.

In 1987 work was begun to recode the multi-basing mode version of CRASOF to FORTRAN using SIMLIB. SIMLIB is based on the concept of linked storage allocation, which makes it easier to manipulate records (Law and Kelton, 1982; 65). The programming changes made to CRASOF, were made to make the program more versatile from a hardware perspective in that it could now be used on stand alone personal computers with sufficient memory. The data files read by the SIMLIB subroutines give analysts using CRASOF the ability to manipulate aircraft forces during the actual run time of the simulation (Neimeyer, 1987). Even though the set-up time for CRASOF simulations runs was reduced, total run time was still at an undesirable level for short notice analysis work (Neimeyer, 1987).

Model Structure

The source code for CRASOF is primarily used to call the different SIMLIB subroutines and input files as well as the user written subroutines.

Program Code. Once the SIMLIB subroutines are initialized, the user written subroutines take over to simulate the scenario desired The user written subroutines can be divided into four sets of subbroutines; flying operations figure 3-1, mission generation figure 3-2, statistic manipulation figure 3-3, and scenario environment figure 3-4.

SUBROUTINE	USE
Search	Look for best aircraft/tanker for the mission.
Plane	Finds closest base with correct mision aircraft.
Gofly	Assigns aircrew and handles report of mission from start to finish.
Seize	Allocates additional resources required for a mission.
Losses	Identifies aircraft attrition.
Arspot	Determines additional refuelings required after tanker is in the air
Artank	Sets up refueling schedule for primary aircraft assigned a mission.
Lastar	Computes distance flown by aircraft and amount of fuel remaining.

Figure 3-1, Flying Operations.

SUBROUTINE	USE
Newmsn	New mission arrival at start of day.
Addmsn	Missions generated from prior missions.
Makecr	generates missions caused by attrition of special mission aircraft.
Flyem	Execute missions scheduled.

Figure 3-2, Mission Generation.

SUBROUTINE	USE
Flush	Attempt made to satisfy all missions built up in the queues.
Stat	Statistics collected on all aspects of a mission.
Release	Releases crews and aircraft after mission completion and maint.
Begday	Beginning of statistics for a given day.
Endday	End of day statistics for a given day

Figure 3-3, Statistic Collection

SUBROUTINE	USE
Wxdelay	Check for weather delay at takeoff.
Wmabort	Check for weather while inflight also mechanical failure.

Figure 3-4, Scenario Environment.

Model Inputs. CRASOF can simulate winter or summer conditions for a given scenario. The theaters that can be modeled with CRASOF are Europe, the Pacific, and Centcom. The initialization data for CRASOF is located in four separate

input data files. To keep this research unclassified, ficticious force sizes were used and located at basing locations within the theaters without reference to actual wartime basing locations.

The first input data file, BASERXX.DAT, is used for bedding down aircraft resources. This data provides longitude and latitude coordinates for basing. The number of aircraft and aircrews per base are also listed. In addition the simulation run time, number of replications and mid-simulation aircraft changes are controlled from this file.

The second input data file, AREAXX.dat, provides theater unique information on mission priorities for the selected theater. Information on special operations and combat rescue ground missions are held in this file. The file stores probabilities used to determine when mission generation will take place. Mission planning information is also held here. This information is based on historical data and is held constant over all simulation runs.

The third data file is ACFTXX.DAT. This data file handles all information on the attributes of each of the aircraft types. A maximum of ten aircraft types can be modeled at once using this data file. Sixty-two attributes are listed to describe the capabilities of each of the aircraft types.

The last data input file used by CRASOF is the climate controlling file, CLIMXX.DAT. This file lists probabilities for ceiling levels, turbulances, visibility, wind, and percipitation. The probabilities are set for individual basing locations and regional areas that cover several bases.

The primary inputs used as factors for the model are the number of each type aircraft. The number of different aircraft used is five. This hypothetical force is shown in figure 3-5.

VARIABLE NAME	AIRCRAFT TYPE
X1	Tilt-roter
X2	Rotary wing
X3	Fixed wing
X4	Rotary wing
X5	Tanker

Figure 3-5 Aircraft Types.

Model Outputs. After completion of a simulation run, statistics are written to an output file. This file holds information on the five measures of capability for each scenario. The five measures are number of successful completions of; infiltration, exfiltration, resupply, combat rescue and refueling missions. Information is also broken out by aircraft type. Figure 3-6 shows the label assignment of each of the five model outputs, and figure 3-7 shows the general flow of the model.

VARIABLE NAME	DESCRIPTION
Y1	Infiltrations
Y2	Exfiltrations
Y3	Resupplies
Y4	Combat Rescues
Y5	Refuelings

Figure 3-6 Response Types.

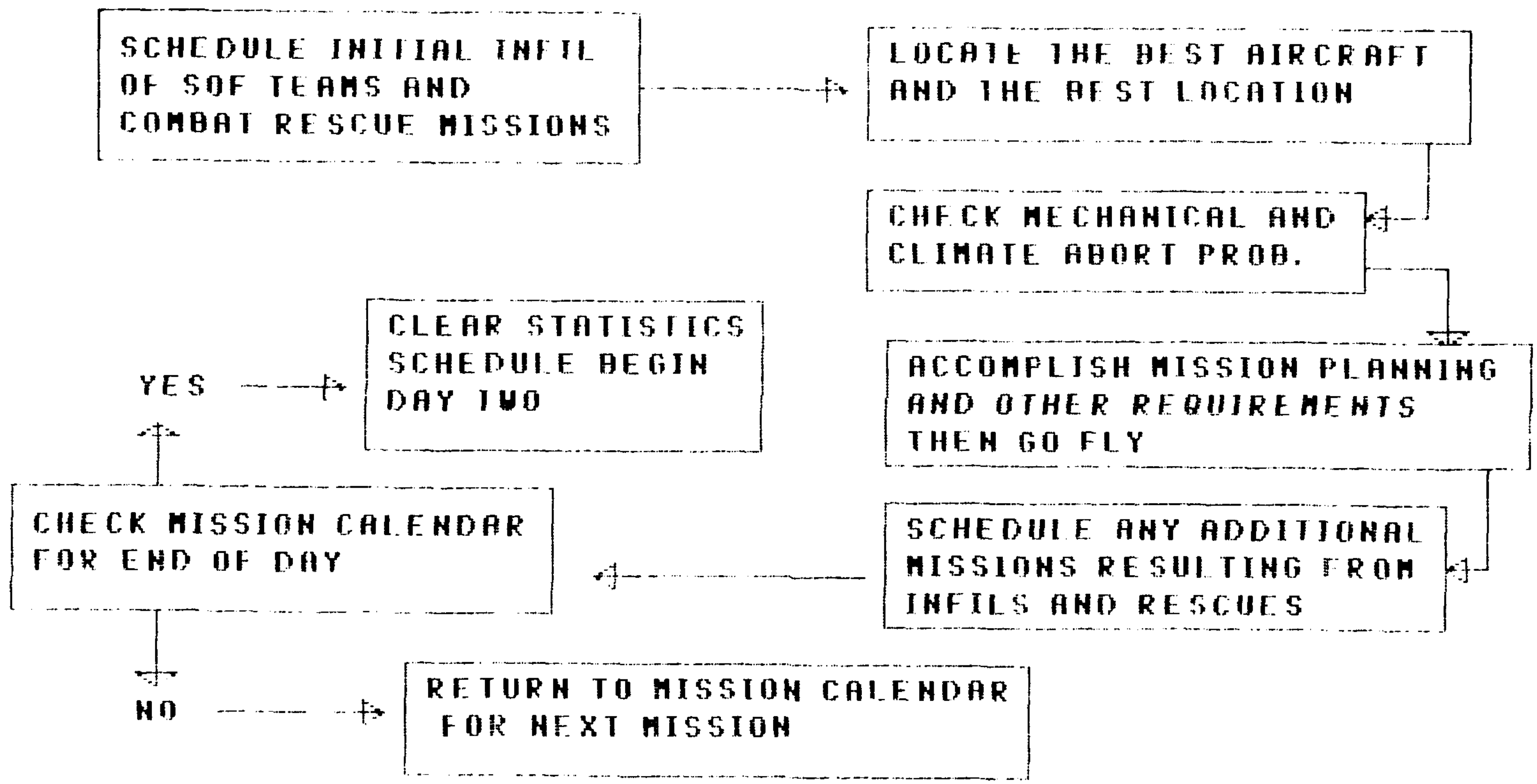

Figure 3-7. CRASOF Flow

SUMMARY

The CRASOF program with its subroutines and data files is well laid out and easy to manipulate. The acceptance of CRASOF as a valid tool for modeling special mission force requirements, has continued through revisions and upgrades using two different simulation languages. The actual program code and data files are not shown in this study due to their length and a desire of Hq MAC/AGS to control the distribution of the CRASOF programming code. If further information on or a copy of CRASOF is desired, The original code is located at Hq MAC/AGS, Scott AFB, Illinois.

IV. RESPONSE SURFACE DESIGNS

Introduction

The force size modeled in each theater is a hypothetical force mix of aircraft to avoid classification of this research. The types of aircraft are listed and described in table 3-5. The time duration for each run of the simulation is sixty days. The climate data is set for summer conditions. Aircraft configurations are listed in appendix A. Each run of the simulation produces five output responses, which are listed in appendix B.

Experimental Design

The design used in each theater is a three level, five factor, fractional factorial (Box and Behnken, 1960; 455). The three levels were chosen to insure that the linear and second order terms would be estimated without being confounded with each other. It is assumed that all terms above the second order are insignificant i.e., the (X1,X2,X3) interaction. Orthogonal blocking is used in the design matrix. The orthogonal blocks refer to the columns of the design matrix being perpendicular so that the colinearity between inputs is zero. The orthogonality "...minimizes the variance of the estimates of regression coefficients," (Box and Behnken, 1960; 457). Center design points (inputs values set to mean value for all inputs) are included in the design matrix to produce replicated runs for testing for lack of fit in the derived regression equations. The center points also eliminate the singularity in the design matrix (Box and Behnken, 1960; 464). The design is listed in tables 4-1(a) and 4-1(b), and is the same for the three theaters modeled in this research.

Table 4-1(a) First Orthogonal Block

RUN	X_1	X_2	X_3	X_4	X_5
1	-1	-1	0	0	0
2	1	-1	0	0	0
3	-1	1	0	0	0
4	1	1	0	0	0
5	0	0	-1	-1	0
6	0	0	1	-1	0
7	0	0	-1	1	0
8	0	0	1	1	0
9	0	-1	0	0	-1
10	0	1	0	0	-1
11	0	-1	0	0	1
12	0	1	0	0	1
13	-1	0	-1	0	0
14	1	0	-1	0	0
15	-1	0	1	0	0
16	1	0	1	0	0
17	0	0	0	-1	-1
18	0	0	0	1	-1
19	0	0	0	-1	1
20	0	0	0	1	1
21	0	0	0	0	0
22	0	0	0	0	0
23	0	0	0	0	0

Table 4-1(b) Second Orthogonal Block

RUN	X_1	X_2	X_3	X_4	X_5
24	0	-1	-1	0	0
25	0	1	-1	0	0
26	0	-1	1	0	0
27	0	1	1	0	0
28	-1	0	0	-1	0
29	1	0	0	-1	0
30	-1	0	0	1	0
31	1	0	0	1	0
32	0	0	-1	0	-1
33	0	0	1	0	-1
34	0	0	-1	0	1
35	0	0	1	0	1
36	-1	0	0	0	-1
37	1	0	0	0	-1
38	-1	0	0	0	1
39	1	0	0	0	1
40	0	-1	0	-1	0
41	0	1	0	-1	0
42	0	-1	0	1	0
43	0	1	0	1	0
44	0	0	0	0	0
45	0	0	0	0	0
46	0	0	0	0	0

European Theater

<u>Scenario Input Data</u>. The number of aircraft modeled covers a range of values feasible for the European theater. Table 4-2 lists aircraft type and the range of values for each aircraft.

Table 4-2 Uncoded European Force Size

A/C Type	Low	Median	High
X_1	10	20	30
X_2	10	15	20
X_3	15	20	25
X_4	15	20	25
X_5	10	15	20

The number of aircraft input per run has been standardized to the values -1, 0, 1 for low, median, and high input values respectively. The conversion equations used for standardizing the number of aircraft input per simulation run are

$$X_1 = (\xi_1 - 20) \div 10 \qquad (4\text{-}1)$$

$$X_2 = (\xi_2 - 15) \div 5 \qquad (4\text{-}2)$$

$$X_3 = (\xi_3 - 20) + 5 \qquad (4\text{-}3)$$

$$X_4 = (\xi_4 - 20) \div 5 \qquad (4\text{-}4)$$

$$X_5 = (\xi_5 - 15) \div 5 \qquad (4\text{-}5)$$

were ξ_i, for $i = 1$ to 5, is the original uncoded value for the corresponding X_i. The coded values are listed below in table 4-3.

Table 4-3 Coded European Force Size

A/C Type	Low	Median	High
X_1	-1	0	1
X_2	-1	0	1
X_3	-1	0	1
X_4	-1	0	1
X_5	-1	0	1

Aircraft capabilities for each aircraft type are listed in appendix A. The output matrix of responses computed by the design inputs are also in appendix B.

Relevent Factors. The SAS statistical package for stepwise regression produced all of the following equations with standard error in parentheses.

Response One. The response equation derived for the infiltration missions was

$$\underset{(2.00)}{\text{INFILS} = 717.0588} + \underset{(3.4)}{43.8125X_2} + \underset{(3.4)}{23.3125X_3} + \underset{(3.4)}{17.375X_5} - \underset{(4.25)}{13.4804X_2^2} - \underset{(4.25)}{15.5637X_5^2} \qquad (4\text{-}6)$$

The alpha level used for entering and removing parameters during the stepwise regression was set to the SAS default value of 0.15. The regression analysis of variance for response one follows:

	DF	Sum Squares	Mean Square	F	Prob>F
Model	5	48005.4253	9601.0851	51.91	0.0001
Error					
pure	5	824.8333	164.9667	1.139	

lck/fit	35	6573.6545	187.8187			
total	40	7398.4878	184.9622			
Total	45	55403.9131				
		B-value	STD Err	II Sum Square	F	Prob>F
Intercept		717.0588				
b1		43.8125	3.4000	30712.5625	166.05	0.0001
b2		23.3125	3.4000	8695.5625	47.01	0.0001
b3		17.375	3.4000	4830.2500	26.11	0.0001
b4		-13.4804	4.2584	1853.5339	10.02	0.0030
b5		-15.5637	4.2584	2470.7414	13.36	0.0007

The multiple correlation coefficient, R^2, equals 0.87. A break-out of the partial R^2 and model R^2 is given for each variable that was included in the regression equation.

	Partial R^2	Model R^2
X_2	0.5543	0.5543
X_3	0.1569	0.7113
X_5	0.0872	0.7985
X_5^2	0.0345	0.8330
X_2^2	0.0335	0.8665

The F-Statistic for the lack of fit test was 1.139 and the F-value for 35 and 5 degrees of freedom is approximately 9.33. Since 1.139 is less than 9.33 there is no significant statistical lack of fit for response equation 4-6. The lack of fit and pure errors can be recombined into total error (Box and Draper, 1981; 41). The total error, $s^2 = 184.96$, can be used as an estimate of the variance , σ^2, for an overall regression significance F-test and as an estimate of model variance $s^2 = 184.96$. The F-statistic for the proposed model should be at least 4 times as large as the f-value found in statistical tables to be considered a good

predictive model, (Box and Draper, 1981; 93). The F-statistic is 51.91 and the F-value from tables is 3.51 at the 99% confidence level. The difference between the two F values is large enough to accept the proposed model as a good predictor of response one.

The final test of adequacy for response equation one is the examination of residual plots. The plot used was a plot of residuals against the predicted values of the response equation. No peculiar patterns showed up in the plot. A list containing residuals, predicted values and residual plots is located in appendix D. A plot of the residuals exihibits no significant peculiar patterns.

Response Two. The response equation produced for exfiltration missions was

$$\underset{(1.81)}{\mathrm{EXFILS} = 351.5588} + \underset{(3.08))}{48.125X_2} + \underset{(3.08)}{23.375X_3} + \underset{(3.08)}{18.0625X_5} - \underset{(3.86)}{15.0637X_2^2} - \underset{(3.86)}{15.4804X_5^2} \qquad (4\text{-}7)$$

The adequacy tests for response equation EXFILS were performed similar to the first response and showed EXFILS to be a good predictive equation.

Response Three. The response equation produced for resupply missions was

$$\mathrm{RESUPPLY} = \underset{(8.51)}{773.1275} - \underset{(14.45)}{22.625X_1} + \underset{(14.45)}{87.0X_2} + \underset{(14.45)}{145.6875X_3} - \underset{(14.45)}{49.3125X_5} + \underset{(18.09)}{77.8480X_3^2} + \underset{(18.09)}{30.8480X_5^2} \qquad (4\text{-}8)$$

The F test for lack of fit and full regression were insignificant so the predicted model is a good one.

Response Four. The response equation produced for combat rescue missions was

$$\text{RESCUES} = \underset{(0.21)}{89.03} + \underset{(0.77)}{4.6875X_1} + \underset{(0.77)}{3.25X_3} \qquad (4\text{-}9)$$

The adequacy tests for response Y_4 showed it to be a good predictive equation although the R^2 value was only 0.56. This fact was counteracted by the relative smallness of residual values.

Response Five. The response equation produced for refueling missions was

$$\text{REFUELS} = \underset{(2.59)}{279.1190} - \underset{(4.21)}{18.125X_1} + \underset{(4.21)}{86.5625X_2} - \underset{(4.21)}{16X_3} + \underset{(4.21)}{14.125X_5}$$
$$+ \underset{(5.35)}{30.2262X_1^2} + \underset{(5.35)}{11.4762X_2^2} + \underset{(5.35)}{16.1429X_4^2} \qquad (4\text{-}10)$$

Pacific Theater

Scenario Input Data. The number of aircraft modeled covers a range of values feasible for the Pacific theater. Table 4-5 lists aircraft type and the range of values for each aircraft.

Table 4-4 Uncoded Pacific Force Size

A/C Type	Low	Median	High
X_1	10	20	30
X_2	5	10	15
X_3	5	15	25
X_4	10	20	30
X_5	15	25	35

The number of aircraft input per run has been standardized to the values -1, 0, 1 for low, median, and high input values respectively. The conversion equations used for standardizing the number of aircraft input per simulation run are

$$X_1 = (\xi_1 - 20) \div 10 \qquad (4\text{-}11)$$

$$X_2 = (\xi_2 - 10) \div 5 \qquad (4\text{-}12)$$

$$X_3 = (\xi_3 - 15) \div 10 \qquad (4\text{-}13)$$

$$X_4 = (\xi_4 - 20) \div 10 \qquad (4\text{-}14)$$

$$X_5 = (\xi_5 - 25) \div 10 \qquad (4\text{-}15)$$

were ξ_i, for $i = 1$ to 5, is the original uncoded value for the corresponding X_i. The coded values are listed in table 4-3.

Table 4-5 Coded Pacific Force Size

A/C Type	Low	Median	High
X_1	-1	0	1
X_2	-1	0	1
X_3	-1	0	1
X_4	-1	0	1
X_5	-1	0	1

Aircraft capabilities for each aircraft type are the same as those for the European forces listed in appendix A. The output matrix of responses derived by the design are listed in appendix B.

<u>Relevent Factors</u>

<u>Response One.</u> The quadratic equation derived for infiltration missions was

$$\text{INFILS} = \underset{(0.512)}{177.9118} + \underset{(1.21)}{24.5625X_2} + \underset{(1.21)}{1.8125X_3} + \underset{(1.21)}{3.0625X_5} - \underset{(1.52)}{17.6127X_2^2} - \underset{(1.52)}{3.9461X_5^2} \qquad (4\text{-}16)$$

The adequacy tests for the first response INFILS showed it to be a good predictor.

Response Two. The response equation produced for exfiltration missions was

$$\begin{aligned}\text{EXFILS} = \underset{(0.49)}{55.8431} + \underset{(0.83)}{12.75X_2} + \underset{(0.83)}{1.937X_5} - \underset{(1.05)}{8.1912X_2^2} \\ - \underset{(1.05)}{3.1078X_5^2} \qquad (4\text{-}17)\end{aligned}$$

The adequacy test showed no statistical problems with the predictor equation.

Response Three. The third response equation for resupply missions was

$$\text{RESUPPLYS} = \underset{(1.75)}{98.3043} + \underset{(2.25)}{38.25X_2} \qquad (4\text{-}18)$$

The adequacy tests showed this equation to be a good predictor.

Response Four. The fourth response equation for combat rescue missions was

$$\begin{aligned}\text{RESCUES} = \underset{(1.02)}{261.4902} + \underset{(1.71)}{46.625X_2} - \underset{(1.71)}{3.875X_5} - \underset{(2.15)}{11.3922X_2^2} \\ + \underset{(2.15)}{4.1078X_5^2} \qquad (4\text{-}19)\end{aligned}$$

Once again the the adequacy tests gave strong indication that the response equation is a good predictor equation.

Response Five. The fifth response equation for refueling missions was

$$\begin{aligned}\text{REFUELS} = \underset{(1.99)}{241.2353} + \underset{(3.39)}{94.4375X_2} + \underset{(3.39)}{13.0625X_5} - \underset{(4.25)}{27.3382X_2^2} \\ - \underset{(4.25)}{11.3382X_5^2} \qquad (4\text{-}20)\end{aligned}$$

The adequacy tests showed this equation to be a good predictor.

<u>Centcom Theater</u>

<u>Scenario Input Data.</u> The number of aircraft modeled covers a range of values feasible for the CENTCOM theater. Table 4-6 lists aircraft type and the range of values for each aircraft.

Table 4-6 Uncoded Centcom Force Size

A/C Type	Low	Median	High
X_1	10	20	30
X_2	5	10	15
X_3	5	15	25
X_4	10	20	30
X_5	15	25	35

The number of aircraft input per run has been standardized to the values -1, 0, 1 for low, median, and high input values respectively. The conversion equations used for standardizing the number of aircraft input per simulation run are

$$X_1 = (\xi_1 - 15) \div 10 \qquad (4\text{-}21)$$

$$X_2 = (\xi_2 - 10) \div 5 \qquad (4\text{-}22)$$

$$X_3 = (\xi_3 - 15) + 5 \qquad (4\text{-}23)$$

$$X_4 = (\xi_4 - 10) \div 5 \qquad (4\text{-}24)$$

$$X_5 = (\xi_5 - 10) + 5 \qquad (4\text{-}25)$$

were ξ_i, for i = 1 to 5, is the original uncoded value for the corresponding X_i. The coded values are listed in table 4-7.

Table 4-7 Coded CENTCOM Force Size

A/C Type	Low	Median	High
X_1	-1	0	1
X_2	-1	0	1
X_3	-1	0	1
X_4	-1	0	1
X_5	-1	0	1

Aircraft capabilities for each aircraft type are similar to those for the European forces. The exceptions are variations in capability for the tilt-roter, (X1), and fixed wing transport, (X3), listed in appendix A. The output matrix of responses derived by the design are listed in appendix B.

Relevent Factors

Response One. The stepwise regression procedure produced the following quadratic equation for infiltration missions

$$\underset{}{INFILS} = \underset{(0.74)}{151.5667} + \underset{(1.25)}{21.375X_1} - \underset{(1.25)}{21.9417X_1^2} \qquad (4\text{-}26)$$

The adequacy tests for the first response had no statistical peculiarities and indications are that the response equation is a good predictive model.

Response Two. The response equation produced for exfiltration missions was

$$EXFILS = \underset{(1.29)}{136.9333} + \underset{(2.18)}{37X_1} - \underset{(2.70)}{37.9333X_1^2} \qquad (4\text{-}27)$$

The adequacy tests for the second response again revealed no peculiarities, indications are that it is a good predictive model.

Response Three. The response for resupply missions was

$$\underset{}{\text{RESUPPLYS}} = \underset{(0.41)}{1.7333} - \underset{(0.69)}{29.9375X_1} - \underset{(0.69)}{2.9375X_3} + \underset{(0.85)}{28.4542X_1^2} \qquad (4\text{-}28)$$

The adequacy tests for the third response gave indications that the surface is a good predictive model.

Response Four. The response equation produced for combat rescue missions was

$$\text{RESCUES} = \underset{(0.43)}{77.9667} + \underset{(0.74)}{24.0625X_1} - \underset{(0.91)}{24.9042X_1^2} \qquad (4\text{-}29)$$

The adequacy tests for the forth response gave indications that it is a good predictive model.

Response Five. The response equation produced for refueling missions was

$$\text{REFUELS} = \underset{(1.86)}{271.8333} + \underset{(3.16)}{64.125X_1} - \underset{(3.92)}{66.4583X_1^2} \qquad (4\text{-}30)$$

The adequacy tests for the fifth response showed no statistical indications that it is not a good predictive model.

V. MULTIVARIATE ANALYSIS

Introduction

In the preceding chapter, response surface equations were derived to predict the number of missions accomplished in each theater of operation. The purpose of this chapter is to reduce the dimensionality of the predicted five responses for each theater based on related mission types. If related missions or dimensions are present, then mission capability indexes, MCI's, can be generated to compare force sizes. The MCI can be used to maximize the utility of the predictive response equations.

Principal component analysis was used initially to get a preliminary idea of the dimensionality present in each of the theaters response data. The principal components analysis reduced the number of variables under study, in this case the five responses. The smaller set of new variables can be described by linear combinations of the original variables while maintaining as much of the variance of the original data as possible (Dillon and Goldstein, 1984; 24). The number resulting from the linear combination of simulated or predicted data can be compared against a baseline force size index to determine whether a new force size produces more capability.

Factor analysis is the next step used in the multivariate analysis of the derived response equations. Factor analysis using the principal component precedure was applied to the original response data to confirm the dimensionality proposed in the principal components analysis. The factor analysis provides an indicator of qualitative communalities present in the responses that make up each derived factor or dimension (Dillon and Goldstein, 1984; 60). Factor analysis can also

extract quantitative differences in the response data however, this is not done in this research due to the common units of measure used to describe the responses and mission capability indexes.

Results

Europe. The eigenvalues and corresponding variance explained from the original response data by the eigenvalues are listed in table 5-1.

Table 5-1 Europe Eigenvalues

	Eigenvalue	Proportion	Cumulative
*PRIN1	16808.9	0.775895	0.77590
*PRIN2	4090.7	0.188828	0.96472
PRIN3	729.2	0.033659	0.99838
PRIN4	28.0	0.001291	0.99967
PRIN5	7.1	0.000327	1.00000

The table reveals that approximately 96.5 percent of the variance in the Europe response data can be explained by the first two principal components, PRIN1 and PRIN2, and the corresponding eigenvalues. The eigenvectors PRIN1 and PRIN2 are those linear combinations of response variables that will generate a value that explains 96.5 percent of the variance for a set of responses. The linear combinations that describe the principal components are listed below.

$$PRIN1 = 0.172330Y_1 + 0.18852642Y_2 + 0.955799Y_3 + 0.026358Y_4 + 0.143227Y_5 \quad (5\text{-}1)$$

$$PRIN2 = 0.323799Y_1 + 0.35877842Y_2 - 0.255051Y_3 + 0.015521Y_4 + 0.837341Y_5 \quad (5\text{-}2)$$

Where Y_1 = INFILS, Y_2 = EXFILS, Y_3 = RESUPPLY, Y_4 = RESCUES, and Y_5 = REFUELS The assumption made here is that there are two underlying dimensions being explained by the five original responses in the European theater.

The factor analysis was used to confirm the existance of two dimensions in the European theater. The factor pattern generated in table 5-2 shows that infiltrations, exfiltrations, resupplies, and combat rescues are loaded most heavily on the first factor. The fifth response, refuelings, is most heavily loaded on factor2.

Table 5-2 Europe Factor Pattern

	FACTOR1	FACTOR2	FACTOR3	FACTOR4	FACTOR5
Y_1	0.63674	0.59022	0.48561	-0.10154	0.00873
Y_2	0.66256	0.62203	0.40444	0.10194	-0.01132
Y_3	0.99096	-0.13045	-0.03118	-0.00069	-0.00036
Y_4	0.75262	0.21864	0.06920	0.22420	0.57507
Y_5	0.31780	0.91658	-0.24261	-0.00477	-0.00002

A varimax rotation was conducted, however when the rotation was complete the factor pattern spread out the responses over four factors. This was uninterpretable for the European theater since it meant that the respomnse were independent of each other which is not the case for infils, exfils, and resupplys. The mission capability indexes that can be formed from the factor analysis are Primary Mission Activities, PMA, and Support Mission Activities, SMA. The PMA responses are infiltration, exfiltration, resupply, and combat rescue missions. The SMA response is air refuelings

generated to support the primary missions.

Pacific. The eigenvalues and corresponding variance explained by the eigenvalues are listed in table 5-3.

Table 5-3 Pacific Eigenvalues

	Eigenvalue	Proportion	Cumulative
*PRIN1	5214.14	0.95946	0.95946
PRIN2	110.96	0.020418	0.97988
PRIN3	83.16	0.015302	0.99518
PRIN4	18.98	0.003492	0.99867
PRIN5	7.2	0.001327	1.00000

The table reveals that approximately 96 percent of the variance in the Pacific response data can be explained by the first principal component, PRIN1, and the corresponding eigenvalue. The eigenvector PRIN1 is the linear combination of response variables that will generate a value that explains 96 percent of the variance for a set of responses. The linear combination that describes the principal component is listed in equation 5-3.

$$\mathrm{PRIN1} = 0.227769Y_1 + 0.117571Y_2 + 0.32077Y_3 + 0.384769Y_4 + 0.826652Y_5 \qquad (5\text{-}3)$$

Where Y_1 = INFILS, Y_2 = EXFILS, Y_3 = RESUPPLY, Y_4 = RESCUES, and Y_5 = REFUELS. The assumption made here is that there is one underlying dimension being explained by the five original responses in the Pacific theater.

The factor analysis is used here to confirm the existance of one dimension in the Pacific theater. The factor pattern in table 5-4 shows that infiltrations, exfiltrations, resupplies, combat rescues, and refuelings, are most heavily loaded on

the first factor.

Table 5-4 Pacific Factor Pattern

	FACTOR1	FACTOR2	FACTOR3	FACTOR4	FACTOR5
Y_1	0.93308	-0.21922	0.20968	0.18949	-0.03778
Y_2	0.91884	-0.25170	0.11259	0.05099	0.27768
Y_3	0.94633	0.14797	-0.27412	0.08576	0.00804
Y_4	0.94830	0.27228	0.16293	-0.00109	0.00605
Y_5	0.99751	-0.06222	-0.01311	-0.02986	-0.00569

The factor pattern was not rotated hear because all factors where loaded on the first factor. The mission capability index that can be formed from the factor analysis is Special Mission Activities, SMA. The SMA responses are infiltration, exfiltration, resupply, combat rescue, and refueling missions.

Centcom. The eigenvalues and corresponding variance explained by the eigenvalues are listed in table 5-5.

Table 5-5 Centcom Eigenvalues

	Eigenvalue	Proportion	Cumulative
*PRIN1	4649.95	0.988316	0.98832
PRIN2	43.16	0.009174	0.99749
PRIN3	7.37	0.001566	0.99906
PRIN4	3.80	0.000807	0.99986
PRIN5	0.64	0.000136	1.00000

The table reveals that approximately 98.8 percent of the variance in the Centcom response data can be explained by the first principal component, PRIN1, and the corresponding eigenvalue. The eigenvector PRIN1 is the linear combination of response

variables that will generate a value that explains 98.8 percent of the variance for a set of responses. The linear combination that describes the principal component is listed in equation 5-4..

$$PRIN1 = 0.0250760Y_1 + 0.436507Y_2 - 0.322881Y_3 + 0.274746Y_4 + 0.752890Y_5 \tag{5-4}$$

Where Y_1 = INFILS, Y_2 = EXFILS, Y_3 = RESUPPLY, Y_4 = RESCUES, and Y_5 = REFUELS. The assumption made here is that there is one underlying dimension being explained by the five original responses in the Centcom theater.

The factor analysis is used here to confirm the existance of one dimension in the Centcom theater. The factor pattern in table 5-6 shows that infiltrations, exfiltrations, resupplies, combat rescues, and refuelings, are most heavily loaded on the first factor. The factor pattern was not rotated because all factors were again loaded on the first factor.

Table 5-6 Centcom Factor Pattern

	FACTOR1	FACTOR2	FACTOR3	FACTOR4	FACTOR5
Y_1	0.99107	0.06054	0.11500	-0.01009	0.02815
Y_2	0.99625	0.05911	-0.05733	-0.02351	0.01223
Y_3	-0.96949	0.24219	-0.00822	0.03691	0.00212
Y_4	0.98856	-0.12177	-0.02704	0.08373	0.01376
Y_5	0.99928	0.03560	0.00853	0.00484	-0.00873

The mission capability index that can be formed from the factor analysis in Centcom is Special Mission Activities, SMA. The SMA responses are infiltration, exfiltration, resupply, combat rescue, and refueling missions. The fact that the Y_3, RESUPPLY, response operates in the opposite direction to the other responses is addressed in the results section.

Summary. The capability indexes generated by the multivariate analysis can be used to compare the aggregate capability generated by proposed force sizes. This comparison is made by reducing the dimensionality of the original five responses into some smaller set of variables while maintaining the maximum amount of variance present in the original data. A demonstration of how the capability indexes can be used is presented in the following chapter.

VI. ANALYSIS RESULTS

Introduction

This chapter summarizes and validates the response surface equations generated in this research. The mission capability indexes derived previously are implemented to provide an example of how they might be used in force sizing analysis. The relevent input factors for each theater and any peculiarities noted in the analysis are also discussed.

Predictive validation was used by comparing the predicted responses against the simulated responses. The second validation step used was to graphically compare the predicted responses with the simulated responses. A determination is then made as to any significant departure in the patterns formed by the plotted points. It should be noted that the significance of variation in the compared patterns is a judgement decision made by the analyst and decision makers. The mission capability indexes will also compare predicted values against simulated values. This will be done to determine the aggregate worth of each force size and whether or not the indexes for the simulated results parallel the indexes for the predicted results.

Response Equation Validation

To conduct the response surface validation, two proposed force sizes are compared in each theater. The same force sizes were used in each theater and are listed in table 6-1. The only difference is found in the capability of aircraft types X1 and X3 for Centcom, where upgrades have been made to account for the increased threats assumed by the analyst in Centcom. The upgrades are the ability to operate in threat type one for X1 and air refueling capability for X3.

Table 6-1 Proposed Forces

Aircraft		Force One	Force Two
tilt-roter	X1	17	25
helicopter1	X2	21	15
transport	X3	30	20
helicopter2	X4	15	15
tanker	X5	20	20

Europe. The response equations for Europe are:

$$\text{INFILS} = 717.0588 + 43.8125X_2 + 23.3125X_3 + 17.375X_5 - 13.4804X_2^2 - 15.5637X_5^2 \quad (4\text{-}11)$$

$$\text{EXFILS} = 351.5588 + 48.125X_2 + 23.375X_3 + 18.0625X_5 - 15.0637X_2^2 - 15.4804X_5^2 \quad (4\text{-}12)$$

$$\text{RESUPPLYS} = 773.1275 - 22.625X_1 + 87.0X_2 + 145.6875X_3 - 49.3125X_5 + 77.8480X_3^2 + 30.8480X_5^2 \quad (4\text{-}13)$$

$$\text{RESCUES} = 89.03 + 4.6875X_1 + 3.25X_3 \quad (4\text{-}14)$$

$$\text{REFUELS} = 279.1190 - 18.125X_1 + 86.5625X_2 - 16X_3 + 14.125X_5 + 30.2262X_1^2 + 11.4762X_2^2 + 16.1429X_4^2 \quad (4\text{-}15)$$

The simulated response values for the two proposed force sizes are found in table 6-2.

Table 6-2 Europe Simulated and Predicted Results

	FORCE 1			FORCE 2		
RESPONSE	SIMUL.	PRED.	DIF	SIMUL.	PRED.	DIF
INFILS	839	799	0.04	724	719	0.007
EXFILS	474	437	0.08	358	354	0.01
RESUPPLY	1238	1455	0.17	816	743	0.09
RESCUE	102	94	0.08	90	91	0.01
REFUEL	381	406	0.07	291	308	0.06

The differences between the predicted and simulated results are plotted in Appendix E. The percentage difference in simulated and predicted responses are all statistically insignificant. It is apparent from the plots that the same trends resulting from the simulated data are mirrored by the predicted responses. In addition, the mission capability indexes follow a similar trend in that the predicted indexes mirror the simulated indexes.

The PMA and SMA indexes for each predicted and simulated force size are listed in table 6-3.

Table 6-3 Mission Capability Indexes

	PMA		SMA	
	FORCE 1	FORCE 2	FORCE 1	FORCE 2
SIMULATED	1564	1016	447	400
PREDICTED	1671	947	386	430

The capability index PMA for force one is greater than force two for both the simulated and predictive models. In the second dimension SMA of the data the simulated index for force one is greater than force two. However, for the predicted model, the SMA

index values are reversed. This descrepancy can be directly attributed to the large number of resupply missions predicted by the response surface for RESUPPLYS. The large difference between the predicted and simulated resupply missions is tolerable in light of the large number of resupply missions accomplished.

Pacific. The response equations for the Pacific are:

$$\text{INFILS} = 177.9118 + 24.5625X_2 + 1.8125X_3 + 3.0625X_5 - 17.6127X_2^2 - 3.9461X_5^2 \quad (4\text{-}16)$$

$$\text{EXFILS} = 55.8431 + 12.75X_2 + 1.937X_5 - 8.1912X_2^2 - 3.1078X_5^2 \quad (4\text{-}17)$$

$$\text{RESUPPLYS} = 98.3043 + 38.25X_2 \quad (4\text{-}18)$$

$$\text{RESCUES} = 261.4902 + 46.625X_2 - 3.875X_5 - 11.3922X_2^2 + 4.1078X_5^2 \quad (4\text{-}19)$$

$$\text{REFUELS} = 241.2353 + 94.4375X_2 + 13.0625X_5 - 27.3382X_2^2 - 11.3382X_5^2 \quad (4\text{-}20)$$

(4.25)

The simulated and predicted response values for the two proposed force sizes are found in table 6-4.

Table 6-4 Pacific Simulated and Predicted Results

	FORCE 1			FORCE 2		
RESPONSE	SIMUL.	PRED.	DIF.	SIMUL.	PRED.	DIF.
INFILS	186	147	0.20	185	183	0.01
EXFILS	57	43	0.24	60	59	0.02
RESUPPLYS	148	182	0.23	132	137	0.04
RESCUES	299	317	0.06	295	302	0.02
REFUELS	310	319	0.03	293	219	0.25

The differences between the predicted and simulated results are plotted in Appendix E. The verification tests which indicated that the response equations were good predictors are validated by the identical trends indicated by the plots for the Pacific hypothetical force sizes.

The PMA index comparison for the predicted and simulated force sizes are listed in table 6-5.

Table 6-5 Mission Capability Indexes

SIMULATED	468	447
PREDICTED	483	456

The capability index PMA for force one is greater than force two for both the simulated and predictive models.

Centcom. The response equations for the Centcom are:

$$INFILS = 151.5667 + 21.375X_1 - 21.9417X_1^2 \qquad (4-26)$$

$$EXFILS = 136.9333 + 37X_1 - 37.9333X_1^2 \quad (4-27)$$

$$RESUPPLYS = 1.7333 - 29.9375X_1 - 2.9375X_3 + 28.4542X_1^2 \quad (4-28)$$

$$RESCUES = 77.9667 + 24.0625X_1 - 24.9042X_1^2 \quad (4-29)$$

$$REFUELS = 271.8333 + 64.125X_1 - 66.4583X_1^2 \quad (4-30)$$

The simulated and predicted response values for the two proposed force sizes are found in table 6-6.

Table 6-6 Centcom Simulated and Predicted Results

	FORCE 1			FORCE 2		
RESPONSE	SIMUL.	PRED.	DIF.	SIMUL.	PRED.	DIF.
INFILS	151	143	0.05	151	157	0.04
EXFILS	136	122	0.10	136	146	0.07
RESUPPLYS	0	9	*	0	21	*
RESCUES	77	69	0.10	79	84	0.06
REFUELS	269	247	0.08	269	287	0.07

The differences between the predicted and simulated results are plotted in Appendix E. The graphical analysis shows similar trends for the Centcom simulated and predicted force capability.

The SMA index for the predicted and simulated force size are listed in table 6-7.

Table 6-7 Centcom Mission Capability Index

	FORCE 1	FORCE 2
SIMULATED	321	321
PREDICTED	291	335

The capability index for force one is the same for the simulated force sizes. However, the SMA index for the predictive force 2 was greater than force 1. This is attributed to the priority assigned to the completion of missions by aircraft types. The most relevent aircraft in Centcom is X1, the modified tilt-rotor. Examination of the simulation output showed that when the number of X1 aircraft increased significantly the overall number of primary missions accomplished by X1 increased. This freed up other aircraft primarily X3, the tanker transport, to do resupply missions. Going from 17 to 25 aircraft reflects this assumption in the predicted index but not in the simulated index.

VII. SUMMARY

Introduction

This chapter summarizes the research completed, observations noted during the research process, and then makes recommendations for using the results and additional research.

Summary of Research

The objective of this research was to explore the feasibility of using response surface metamodels in conjunction with CRASOF. The goal was to enhance the force sizing capability at Headquarters Military Airlift Command. This research was accomplished by applying multiple regression analysis to simulated output data to form metamodels that predicted the output responses generated by CRASOF. Indexes were also derived which reduced the dimensionality of the responses that enhanced the comparison of different force sizes. The response metamodels combined with the mission capability indexes showed enormous potential for expediting answers to decision makers on whether further detailed study of proposed force sizes are warranted.

Observations

The utility of this research was in describing the methodology to use on real-world special mission force sizes. Given real world force structures, the methodology described in this research can easily be applied to produce metamodels to supplement future CRASOF force sizing exercises. The relevent aircraft described in each theater can also help in determining the driving forces necessary for mission success in each of the given theaters.

Recommendations

This research suggests a methodology appropriate for use in force sizing analysis. The metamodels can be used to minimize start up time when simulation runs are the only method of determining force capability. The metamodels only expose trends in the output data and are not meant to supplant CRASOF, only supplement it. Caution should be taken to avoid labeling metamodel predictions as exact capability.

Future Research

Several indications in the research showed that the resupply mission had negative impact on the dimensionality in the high threat Centcom theater of operation. An assumption was made that this was due to the lower priority placed on resupply missions. Consequently, when a resupply was accomplished it took away resources from higher priority missions that could have been done. Future research could focus in on the priorities assigned to the missions to determine if priority of mission has a significant impact across the spectrum of theaters.

Another possible area for research is to investigate the confidence intervals for which the predicted equations are statistically valid using the classified input data located at Hq MAC. This study could also examine extrapolating responses from inputs that are outside the design points low and high settings.

There are a number of other topics that can be investigated using CRASOF. The inputs to the model, i.e., the settings which describe the theater climate are easily manipulated with a text editor. Investigation into affects on mission capability resulting from manipulation of various inputs might yield additional insight into factors affecting mission capability in the special missions environment.

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APPENDIX A: Aircraft Input Capability

AIRCRAFT CHARACTERISTICS (3X,A25,3X,5F9.0):

NOTE: ITEM 2, CAPABILITY/REQUIREMENTS ENTRY CODE FOLLOWS
0 - CAPABILITY MODE FOR ACFT & CREW
1 - REQUIREMENT MODE FOR ACFT; CAPABILITY MODE FOR CREW
2 - CAPABILITY MODE FOR ACFT; REQUIREMENT MODE FOR CREW
3 - REQUIREMENT MODE FOR ACFT & CREW

		AIRCRAFT TYPES				
ITEM#		X1	N/A	N/A	N/A	X2
1	NOT USED	.00	.00	.00	.12	.00
2	CAP/REQ'T V1-3; SEE NOTE)	.00	.00	.00	.00	.00
3	THREAT TYPE (1-3)	1.00	2.00	2.00	3.00	2.00
4	1ST PRIORITY MSN (1-5)	2.00	4.00	4.00	4.00	2.00
5	2ND PRIORITY MISSION #	1.00	.00	.00	.00	1.00
6	3RD PRIORITY MISSION #	3.00	.00	.00	.00	3.00
7	4TH PRIORITY MISSION #	4.00	.00	.00	.00	4.00
8	5TH PRIORITY MISSION #	.00	.00	.00	.00	.00
9	NOT USED	.00	.00	.00	.00	.00
10	NOT USED	.00	.00	.00	.00	.00
11	NOT USED	.00	.00	.00	.00	.00
12	NOT USED	.00	.00	.00	.00	.00
13	NOT USED	.00	.00	.00	.00	.00
14	ATTRITION RATE (%)	.10	.10	.10	.10	.10
15	MECH AIR ABORT (%)	.00	.00	.00	.00	.00
16	UTE RATE (HRS/DAY/ACFT)	3.00	2.20	2.00	1.68	2.33
17	SURGE RATE (HRS/DAY/ACFT)	.00	.00	.00	.00	.00
18	DAYS CAN SUSTAIN SURGE	.00	.00	.00	.00	.00
19	MISSION EFFECTIVENESS (%)	95.00	95.00	95.00	95.00	95.00
20	MISSION CAPABLE RATE (%)	72.00	77.50	58.50	64.50	58.50
21	CRASH HAS SURVIVORS (%)	75.00	75.00	75.00	75.00	75.00
22	VTOL CAPABLE (Y=1,N=0)	1.00	1.00	1.00	1.00	1.00
23	AVG CRUISE (KTAS)	220.00	120.00	120.00	120.00	120.00
24	UNREFUELED RADIUS (NM)	600.00	300.00	285.00	290.00	290.00
25	REFUEL INFLIGHT(Y=1,N=0)	1.00	1.00	1.00	1.00	1.00
26	REQ'D A/R TRACK (NM)	100.00	30.00	30.00	30.00	30.00
27	RADII BEFORE A/R (0.5-2.0)	1.50	1.25	1.25	1.25	1.25
28	BURN RATE (LBS/HR)	2300.00	1200.00	2200.00	1200.00	2200.00
29	MAX FUEL (LBS)	16500.00	6000.00	11800.00	6500.00	11800.00

30 BURN LBS FUEL BEFORE A/R	.00	.00	.00	.00	.00
31 DISTANCE FROM FOL (NM)	.00	.00	.00	.00	.00
32 NOT USED	.00	.00	.00	.00	.00
33 MAX FLY HRS W/O AUGMENTING	9.00	10.00	10.00	10.00	10.00
34 CREW RATIO	2.00	1.50	1.50	1.25	1.50
35 AVG ACFT TURN TIME (HRS)	1.00	1.00	2.00	1.00	2.00
36 TAKEOFF CEILING MIN (FT)	.00	300.00	300.00	300.00	.00
37 TAKEOFF VIS MIN (SM)	.12	1.00	1.00	1.00	.00
38 ACFT #1 MSN CEILING MIN	100.00	300.00	300.00	300.00	100.00
39 ACFT #1 MSN VIS MIN	.25	1.00	1.00	1.00	.25
40 ACFT #1 MSN WIND MAX	45.00	45.00	45.00	60.00	45.00
41 RAIN CNX #1 MSN (Y=1,N=0)	1.00	1.00	1.00	1.00	1.00
42 TURB CNX					
43 ACFT #2 MSN CEILING MIN	.00	300.00	300.00	300.00	100.00
44 ACFT #2 MSN VIS MIN	.00	1.00	1.00	1.00	.25
5 ACFT #2 MSN WIND MAX	45.00	45.00	45.00	60.00	45.00
6 RAIN CNX #2 MSN (Y=1,N=0)	1.00	1.00	1.00	1.00	1.00
7 TURB CNX #2 MSN (Y=1,N=0)	.00	1.00	1.00	1.00	.00
8 ACFT #3 MSN CEILING MIN	100.00	300.00	300.00	300.00	.00
9 ACFT #3 MSN VIS MIN	.25	1.00	1.00	1.00	.00
0 ACFT #3 MSN WIND MAX	45.00	45.00	45.00	60.00	45.00
1 RAIN CNX #3 MSN (Y=1,N=0)	1.00	1.00	1.00	1.00	1.00
2 TURB CNX #3 MSN (Y=1,N=0)	.00	1.00	1.00	1.00	.00
3 ACFT #4 MSN CEILING MIN	100.00	300.00	300.00	300.00	100.00
4 ACFT #4 MSN VIS MIN	.25	1.00	1.00	1.00	.25
5 ACFT #4 MSN WIND MAX	45.00	45.00	45.00	60.00	45.00
6 RAIN CNX #4 MSN (Y=1,N=0)	1.00	1.00	1.00	1.00	1.00
7 TURB CNX #4 MSN (Y=1,N=0)	.00	1.00	1.00	1.00	.00
8 ACFT #5 MSN CEILING MIN	100.00	300.00	300.00	300.00	100.00
9 ACFT #5 MSN VIS MIN	.25	1.00	1.00	1.00	.25
0 ACFT #5 MSN WIND MAX	45.00	45.00	45.00	60.00	45.00
1 RAIN CNX #5 MSN (Y=1,N=0)	1.00	1.00	1.00	1.00	1.00
2 TURB CNX #5 MSN (Y=1,N=0)	.00	1.00	1.00	1.00	.00

			AIRCRAFT TYPES		
ITEM#	X3	N/A	X4	X5	N/A
1 NOT USED	.00	.00	.00	.00	.00
2 CAP/REQ'T (0-3; SEE NOTE	.00	.00	.00	.00	.00
3 THREAT TYPE (1-3)	1.00	1.00	2.00	2.00	1.00
4 1ST PRIORITY MSN (1-5)	1.00	2.00	2.00	5.00	1.00
5 2ND PRIORITY MISSION #	3.00	1.00	1.00	.00	3.00
6 3RD PRIORITY MISSION #	.00	3.00	3.00	.00	5.00
7 4TH PRIORITY MISSION #	.00	4.00	4.00	.00	.00

8 5TH PRIORITY MISSION #	.00	.00	.00	.00	.00
9 NOT USED	.00	.00	.00	.00	.00
10 NOT USED	.00	.00	.00	.00	.00
11 NOT USED	.00	.00	.00	.00	.00
12 NOT USED	.00	.00	.00	.00	.00
13 NOT USED	.00	.00	.00	.00	.00
14 ATTRITION RATE (%)	.10	.10	.10	.10	.10
15 MECH AIR ABORT (%)	.43	.00	.00	2.44	.43
16 UTE RATE (HRS/DAY/ACFT)	3.00	2.33	2.20	2.80	3.00
17 SURGE RATE (HRS/DAY/ACFT)	.00	.00	.00	.00	.00
18 DAYS CAN SUSTAIN SURGE	.00	.00	.00	.00	.00
19 MISSION EFFECTIVENESS (%)	95.00	95.00	95.00	95.00	95.00
20 MISSION CAPABLE RATE (%)	61.50	58.50	77.50	64.50	61.50
21 CRASH HAS SURVIVORS (%)	15.00	75.00	75.00	15.00	15.00
22 VTOL CAPABLE (Y=1,N=0)	.00	1.00	1.00	.00	.00
23 AVG CRUISE (KTAS)	220.00	120.00	120.00	220.00	220.00
24 UNREFUELED RADIUS (NM)	950.00	290.00	300.00	1350.00	950.00
25 REFUEL INFLIGHT(Y=1,N=0)	.00	1.00	1.00	.00	.00
26 REQ'D A/R TRACK (NM)	.00	30.00	30.00	.00	.00
27 RADII BEFORE A/R (0.5-2.0)	.00	1.25	1.25	.00	.00
28 BURN RATE (LBS/HR)	6000.00	2200.00	1200.00	6000.00	6000.00
29 MAX FUEL (LBS)	59000.00	11800.00	6000.00	82000.00	59000.00
30 BURN LBS FUEL BEFORE A/R	.00	.00	.00	.00	.00
31 DISTANCE FROM FOL (NM)	.00	.00	.00	.00	.00
32 NOT USED					
33 MAX FLY HRS W/O AUGMENTING	9.00	10.00	10.00	9.00	9.00
34 CREW RATIO	1.50	1.50	1.50	1.50	1.50
35 AVG ACFT TURN TIME (HRS)	1.50	2.00	1.00	1.50	1.50
6 TAKEOFF CEILING MIN (FT)	.00	.00	300.00	.00	.00
7 TAKEOFF VIS MIN (SM)	.30	.00	1.00	.30	.30
8 ACFT #1 MSN CEILING MIN	.00	100.00	300.00	.00	.00
9 ACFT #1 MSN VIS MIN	.00	.25	1.00	1.00	.00
0 ACFT #1 MSN WIND MAX	60.00	45.00	45.00	60.00	60.00
1 RAIN CNX #1 MSN (Y=1,N=0)	1.00	1.00	1.00	1.00	1.00
2 TURB CNX #1 MSN (Y=1,N=0)	1.00	.00	1.00	1.00	1.00
3 ACFT #2 MSN CEILING MIN	.00	100.00	300.00	.00	.00
4 ACFT #2 MSN VIS MIN	.00	.25	1.00	.00	.00
5 ACFT #2 MSN WIND MAX	60.00	45.00	45.00	60.00	60.00
6 RAIN CNX #2 MSN (Y=1,N=0)	1.00	1.00	1.00	1.00	1.00
7 TURB CNX #2 MSN (Y=1,N=0)	1.00	.00	1.00	1.00	1.00
8 ACFT #3 MSN CEILING MIN	500.00	.00	300.00	.00	.00
9 ACFT #3 MSN VIS MIN	1.00	.00	1.00	.00	1.00
0 ACFT #3 MSN WIND MAX	60.00	45.00	45.00	60.00	60.00

1 RAIN CNX #3 MSN (Y=1,N=0)	1.00	1.00	1.00	1.00	1.00
2 TURB CNX #3 MSN (Y=1,N=0)	1.00	.00	1.00	1.00	1.00
3 ACFT #4 MSN CEILING MIN	500.00	100.00	300.00	.00	.00
4 ACFT #4 MSN VIS MIN	1.00	.25	1.00	.00	.00
5 ACFT #4 MSN WIND MAX	60.00	45.00	45.00	60.00	60.00
6 RAIN CNX #4 MSN (Y=1,N=0)	1.00	1.00	1.00	1.00	1.00
7 TURB CNX #4 MSN (Y=1,N=0)	1.00	.00	1.00	1.00	1.00
8 ACFT #5 MSN CEILING MIN	.00	100.00	300.00	.00	.00
9 ACFT #5 MSN VIS MIN	.00	.25	1.00	.00	.00
0 ACFT #5 MSN WIND MAX	60.00	45.00	45.00	60.00	60.00
1 RAIN CNX #5 MSN (Y=1,N=0)	1.00	1.00	1.00	1.00	1.00
2 TURB CNX #5 MSN (Y=1,N=0)	1.00	.00	1.00	1.00	1.00

APPENDIX B:
Europe Response Matrix and Box Benhken Fractional Factorial Design

Y1= INFILTRATION Y2= EXFILTRATION Y3= RESUPPLY Y4= RESCUE Y5= REFUEL

Y1	Y2	Y3	Y4	Y5	mu	X1	X2	X3	X4	X5
655	291	785	86	266	1	-1	-1	0	0	0
657	285	742	86	196	1	1	-1	0	0	0
758	397	917	95	400	1	-1	1	0	0	0
755	389	893	93	385	1	1	1	0	0	0
679	311	740	87	308	1	0	0	-1	-1	0
762	389	1016	91	285	1	0	0	1	-1	0
662	328	706	87	314	1	0	0	-1	1	0
738	377	1055	90	284	1	0	0	1	1	0
640	273	754	86	197	1	0	-1	0	0	-1
699	337	978	99	324	1	0	1	0	0	-1
669	296	757	85	208	1	0	-1	0	0	1
770	407	852	97	413	1	0	1	0	0	1
692	324	698	85	342	1	-1	0	-1	0	0
697	324	667	88	314	1	1	0	-1	0	0
750	383	969	94	315	1	-1	0	1	0	0
746	385	897	93	294	1	1	0	1	0	0
693	323	927	93	283	1	0	0	0	-1	-1
699	321	941	89	278	1	0	0	0	1	-1
711	343	776	90	286	1	0	0	0	-1	1
729	361	737	91	296	1	0	0	0	1	1
709	347	757	92	304	1	0	0	0	0	0
703	327	728	86	257	1	0	0	0	0	0
720	339	719	80	266	1	0	0	0	0	0
650	278	580	83	211	1	0	-1	-1	0	0
731	366	844	89	409	1	0	1	-1	0	0
671	298	995	88	189	1	0	-1	1	0	0
769	401	1082	100	349	1	0	1	1	0	0
717	362	858	91	320	1	-1	0	0	-1	0
728	368	774	90	291	1	1	0	0	-1	0
714	358	860	90	363	1	-1	0	0	1	0
723	359	793	93	295	1	1	0	0	1	0
676	308	796	87	293	1	0	0	-1	0	-1
697	343	1041	93	257	1	0	0	1	0	-1
708	345	673	87	310	1	0	0	-1	0	1
735	382	980	96	272	1	0	0	1	0	1
685	311	773	86	314	1	-1	0	0	0	-1
657	298	772	91	289	1	1	0	0	0	-1

703	340	729	85	355	1	-1	0	0	0	1
699	329	689	87	321	1	1	0	0	0	1
646	274	563	83	225	1	0	-1	0	-1	0
735	376	806	90	437	1	0	1	0	-1	0
659	281	605	80	233	1	0	-1	0	1	0
731	373	801	89	393	1	0	1	0	1	0
725	353	750	82	279	1	0	0	0	0	0
735	361	755	91	269	1	0	0	0	0	0
733	362	773	94	276	1	0	0	0	0	0

Pacific Response Matrix with Box and Behnken Design

Y1	Y2	Y3	Y4	Y5	MU	X1	X2	X3	X4	X5
131	37	56	204	117	1	-1	-1	0	0	0
128	34	65	203	115	1	1	-1	0	0	0
185	61	142	304	321	1	-1	1	0	0	0
187	60	149	298	322	1	1	1	0	0	0
178	57	97	261	243	1	0	0	-1	-1	0
176	56	94	262	239	1	0	0	1	-1	0
177	57	97	263	239	1	0	0	-1	1	0
178	58	95	261	239	1	0	0	1	1	0
131	30	65	208	112	1	0	-1	0	0	-1
169	54	109	284	232	1	0	1	0	0	-1
134	33	57	202	119	1	0	-1	0	0	1
187	61	144	310	336	1	0	1	0	0	1
176	53	87	263	228	1	-1	0	-1	0	0
178	54	101	258	241	1	1	0	-1	0	0
179	53	99	259	234	1	-1	0	1	0	0
179	58	95	265	239	1	1	0	1	0	0
174	47	109	275	223	1	0	0	0	-1	-1
171	52	100	276	223	1	0	0	0	1	-1
177	55	96	262	240	1	0	0	0	-1	1
174	54	94	261	235	1	0	0	0	1	1
173	56	103	254	235	1	0	0	0	0	0
158	47	85	276	218	1	0	0	0	0	0
180	65	112	252	260	1	0	0	0	0	0
135	36	64	208	118	1	0	-1	-1	0	0
185	61	137	295	310	1	0	1	-1	0	0
141	31	60	205	118	1	0	-1	1	0	0
185	60	137	293	302	1	0	1	1	0	0
180	49	97	259	230	1	-1	0	0	-1	0
176	51	97	259	233	1	1	0	0	-1	0

185	53	90	266	235	1	-1	0	0	1	0
177	57	98	261	239	1	1	0	0	1	0
169	51	94	268	212	1	0	0	-1	0	-1
175	48	93	280	218	1	0	0	1	0	-1
167	53	91	267	225	1	0	0	-1	0	1
181	54	96	260	242	1	0	0	1	0	1
170	54	94	270	230	1	-1	0	0	0	-1
173	54	93	272	230	1	1	0	0	0	-1
180	55	96	253	243	1	-1	0	0	0	1
181	56	103	256	249	1	1	0	0	0	1
139	38	61	201	118	1	0	-1	0	-1	0
187	61	138	302	312	1	0	1	0	-1	0
139	34	59	205	116	1	0	-1	0	1	0
186	59	143	296	309	1	0	1	0	1	0
183	57	101	245	268	1	0	0	0	0	0
180	59	136	273	258	1	0	0	0	0	0
185	65	93	257	253	1	0	0	0	0	0

Centcom Response Matrix with Box and Behnken Fractional Factorial

Y1	Y2	Y3	Y4	Y5	mu	X1	X2	X3	X4	X5
111	61	64	26	143	1	-1	-1	0	0	0
151	136	0	77	268	1	1	-1	0	0	0
111	56	64	32	140	1	-1	1	0	0	0
151	136	0	77	268	1	1	1	0	0	0
151	136	5	77	272	1	0	0	-1	-1	0
151	136	0	79	269	1	0	0	1	-1	0
148	133	11	77	268	1	0	0	-1	1	0
151	136	0	77	270	1	0	0	1	1	0
151	136	0	77	270	1	0	-1	0	0	-1
151	136	1	77	270	1	0	1	0	0	-1
151	136	0	78	269	1	0	-1	0	0	1
151	136	0	78	269	1	0	1	0	0	1
109	64	59	28	141	1	-1	0	-1	0	0
151	136	0	77	271	1	1	0	-1	0	0
109	56	51	33	135	1	-1	0	1	0	0
151	136	0	77	270	1	1	0	1	0	0
151	136	0	78	270	1	0	0	0	-1	-1
151	136	0	77	270	1	0	0	0	1	-1
151	136	0	80	270	1	0	0	0	-1	1
151	136	0	77	268	1	0	0	0	1	1
151	136	1	79	272	1	0	0	0	0	0
158	140	3	77	282	1	0	0	0	0	0

164	146	3	76	290	1	0	0	0	0	0
151	136	4	78	271	1	0	−1	−1	0	0
151	136	5	80	271	1	0	1	−1	0	0
151	136	0	77	270	1	0	−1	1	0	0
151	136	0	77	270	1	0	1	1	0	0
108	62	61	27	141	1	−1	0	0	−1	0
151	136	0	78	269	1	1	0	0	−1	0
106	70	54	30	147	1	−1	0	0	1	0
151	136	0	78	269	1	1	0	0	1	0
151	136	9	73	270	1	0	0	−1	0	−1
151	136	1	77	270	1	0	0	1	0	−1
151	136	6	78	272	1	0	0	−1	0	1
151	136	0	77	270	1	0	0	1	0	1
108	56	68	26	137	1	−1	0	0	0	−1
151	136	2	76	271	1	1	0	0	0	−1
104	71	60	30	146	1	−1	0	0	0	1
151	136	0	77	270	1	1	0	0	0	1
151	136	1	77	270	1	0	−1	0	−1	0
151	136	1	79	271	1	0	1	0	−1	0
151	136	0	77	270	1	0	−1	0	1	0
151	136	1	76	270	1	0	1	0	1	0
147	122	0	76	255	1	0	0	0	0	0
133	118	0	79	236	1	0	0	0	0	0
173	185	0	94	340	1	0	0	0	0	0

APPENDIX C: Multiple Regression ANOVA Tables

--------------------- REGRESSION ANALYSIS ---------------------

HEADER DATA FOR: B:EUR LABEL:
NUMBER OF CASES: 46 NUMBER OF VARIABLES: 16

EUROPE INFILTRATION (Y1) REGRESSION

INDEX	NAME	MEAN	STD.DEV.
1	x2	.0000	.5963
2	x3	7.60870E-16	.5963
3	x5	3.39130E-15	.5963
4	x2s	.3478	.4815
5	x5s	.3478	.4815
DEP. VAR.:	infil	706.9565	35.0884

DEPENDENT VARIABLE: infil

VAR.	REGRESS COEFF	STD. ERROR	T(DF= 40)	PROB.	PART r^2
x2	43.8125	3.4000	12.886	.00000	.8059
x3	23.3125	3.4000	6.857	.00000	.5403
x5	17.3750	3.4000	5.110	.00001	.3950
x2s	-13.4804	4.2584	-3.166	.00296	.2003
x5s	-15.5637	4.2584	-3.655	.00074	.2503
CONSTANT	717.0588				

STD. ERROR OF EST. = 13.6001

ADJUSTED R SQUARED = .8498
R SQUARED = .8665
MULTIPLE R = .9308

ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F RATIO	PROB.
REGRESSION	48005.4253	5	9601.0851	51.908	.000E+00
RESIDUAL	7398.4877	40	184.9622		
LACK OF FIT	6573.6544	35	187.8187	1.14	
PURE ERR	824.8333	5	164.9667		
TOTAL	55403.9130	45			

-------------------- REGRESSION ANALYSIS --------------------

HEADER DATA FOR: B:EUR   LABEL:
NUMBER OF CASES: 46   NUMBER OF VARIABLES: 16

EUROPE EXFILTRATION (Y2) REGRESSION

INDEX	NAME	MEAN	STD. DEV.
1	x2	.0000	.5963
2	x3	7.60870E-16	.5963
3	x5	3.39130E-15	.5963
4	x2s	.3478	.4815
5	x5s	.3478	.4815
DEP. VAR.:	exfil	340.9348	36.8905

DEPENDENT VARIABLE: exfil

VAR.	REGRESS COEFF	STD. ERROR	T(DF= 40)	PROB.	PART r^2
x2	48.1250	3.0832	15.609	.00000	.8590
x3	23.3750	3.0832	7.581	.00000	.5897
x5	18.0625	3.0832	5.858	.00000	.4618
x2s	-15.0637	3.8615	-3.901	.00036	.2756
x5s	-15.4804	3.8615	-4.009	.00026	.2866
CONSTANT	351.5588				

STD. ERROR OF EST. = 12.3327

ADJUSTED R SQUARED = .8882
R SQUARED = .9007
MULTIPLE R = .9490

ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F RATIO	PROB.
REGRESSION	55157.0041	5	11031.4008	72.530	.000E+00
RESIDUAL	6083.8002	40	152.0950		
LACK FIT	5170.9669	35	147.7419	0.809	
PURE ERROR	912.8333	5	182.5667		
TOTAL	61240.8043	45			

-------------------- REGRESSION ANALYSIS --------------------

HEADER DATA FOR: B:EUR LABEL:
NUMBER OF CASES: 46 NUMBER OF VARIABLES: 16

EUROPE RESUPPLY (Y3) REGRESSION

INDEX	NAME	MEAN	STD. DEV.
1	x1	1.69565E-15	.5963
2	x2	.0000	.5963
3	x3	7.60870E-16	.5963
4	x5	3.39130E-15	.5963
5	x3s	.3478	.4815
6	x5s	.3478	.4815
DEP. VAR.:	resup	810.9348	125.0483

DEPENDENT VARIABLE: resup

VAR.	REGRESS COEFF	STD. ERROR	T(DF= 39)	PROB.	PART r^2
x1	-22.6250	14.4459	-1.566	.12538	.0592
x2	87.0000	14.4459	6.022	.00000	.4819
x3	145.6875	14.4459	10.085	.00000	.7228
x5	-49.3125	14.4459	-3.414	.00151	.2300
x3s	77.8480	18.0928	4.303	.00011	.3219
x5s	30.8480	18.0928	1.705	.09615	.0694
CONSTANT	773.1275				

STD. ERROR OF EST. = 57.7837

ADJUSTED R SQUARED = .7865
R SQUARED = .8149
MULTIPLE R = .9027

ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F RATIO	PROB.
REGRESSION	573449.6107	6	95574.9351	28.624	7.700E-13
RESIDUAL	130219.1936	39	3338.9537		
LACK FIT	128225.1936	34	3771.3292	9.46	
PURE	1994.0000	5	398.8000		
TOTAL	703668.8043	45			

REGRESSION ANALYSIS

HEADER DATA FOR: B:EUR   LABEL:
NUMBER OF CASES: 46   NUMBER OF VARIABLES: 16

EUROPE RESCUE (Y4) REGRESSION

INDEX	NAME	MEAN	STD. DEV.
1	x2	.0000	.5963
2	x3	7.60870E-16	.5963
DEP. VAR.:	rescu	89.3043	4.5405

DEPENDENT VARIABLE: rescu

VAR.	REGRESS COEFF	STD. ERROR	T(DF= 43)	PROB.	PART r^2
x2	4.6875	.7693	6.093	.00000	.4634
x3	3.2500	.7693	4.225	.00012	.2933
CONSTANT	89.3043				

STD. ERROR OF EST. = 3.0772

ADJUSTED R SQUARED = .5407
R SQUARED = .5611
MULTIPLE R = .7491

ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F RATIO	PROB.
REGRESSION	520.5625	2	260.2813	27.487	2.045E-08
RESIDUAL	407.1766	43	9.4692		
LACK FIT	243.6766	38	6.4125	0.196	
PURE ERR	163.5000	5	32.7000		
TOTAL	927.7391	45			

-------------------- REGRESSION ANALYSIS --------------------

HEADER DATA FOR: B:EUR   LABEL:
NUMBER OF CASES: 46   NUMBER OF VARIABLES: 16

EUROPE REFUELING (Y5) REGRESSION

INDEX	NAME	MEAN	STD. DEV.
1	x1	1.69565E-15	.5963
2	x2	.0000	.5963
3	x3	7.60870E-16	.5963
4	x5	3.39130E-15	.5963
5	x1s	.3478	.4815
6	x2s	.3478	.4815
7	x4s	.3478	.4815
DEP. VAR.:	refuel	299.2391	58.4295

DEPENDENT VARIABLE: refuel

VAR.	REGRESS COEFF	STD. ERROR	T(DF= 38)	PROB.	PART r^2
x1	-18.1250	4.2074	-4.308	.00011	.3281
x2	86.5625	4.2074	20.574	.00000	.9176
x3	-16.0000	4.2074	-3.803	.00050	.2757
x5	14.1250	4.2074	3.357	.00180	.2287
x1s	30.2262	5.3536	5.646	.00000	.4562
x2s	11.4762	5.3536	2.144	.03852	.1079
x4s	16.1429	5.3536	3.015	.00456	.1931
CONSTANT	279.1190				

STD. ERROR OF EST. = 16.8297

ADJUSTED R SQUARED = .9170
R SQUARED = .9299
MULTIPLE R = .9643

ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F RATIO	PROB.
REGRESSION	142867.2416	7	20409.6059	72.058	1.700E-13
RESIDUAL	10763.1280	38	283.2402		
LACK FIT	9464.2947	33	286.7968	1.104	
PURE ERR	1298.8333	5	259.7667		
TOTAL	153630.3696	45			

REGRESSION ANALYSIS

HEADER DATA FOR: C:PAC LABEL:
NUMBER OF CASES: 46 NUMBER OF VARIABLES: 16

PACIFIC INFILTRATION (Y1) REGRESSION

INDEX	NAME	MEAN	STD. DEV.
1	x2	.0000	.5963
2	x3	7.60870E-16	.5963
3	x5	3.39130E-15	.5963
4	x2s	.3478	.4815
5	x5s	.3478	.4815
DEP. VAR.:	infil	170.4130	17.6265

DEPENDENT VARIABLE: Y1

VAR.	REGRESS COEFF	STD. ERROR	T(DF=40)	PROB.	PARTIAL r^2
x2	24.5625	1.2142	20.229	.00000	.9110
x3	1.8125	1.2142	1.493	.14336	.0528
x5	3.0625	1.2142	2.522	.01575	.1372
x2s	-17.6127	1.5208	-11.582	.00000	.7703
x5s	-3.9461	1.5208	-2.595	.01317	.1441
CONSTANT	177.9118				

STD. ERROR OF EST. = 4.8569

ADJUSTED R SQUARED = .9241
R SQUARED = .9325
MULTIPLE R = .9657

ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F RATIO	PROB.
REGRESSION	13037.5652	5	2607.5130	110.536	3.000E-14
RESIDUAL	943.5870	40	23.5897		
LACK OF FIT	450.0870	35	12.8596	0.130	
PURE ERROR	493.5000	5	98.7000		
TOTAL	13981.1522	45			

------------------ REGRESSION ANALYSIS --------------------

HEADER DATA FOR: C:PAC LABEL:
NUMBER OF CASES: 46 NUMBER OF VARIABLES: 16

PACIFIC EXFILTRATION (Y2) REGRESSION

INDEX	NAME	MEAN	STD.DEV.
1	x2	.0000	.5963
2	x5	3.39130E-15	.5963
3	x2s	.3478	.4#5
4	x5s	.3478	.4815
DEP. VAR.:	exfil	51.9130	9.2396

DEPENDENT VARIABLE: Y2

VAR.	REGRESS COEFF	STD. ERROR	T(DF=41)	PROB.	PARTIAL r^2
x2	12.7500	.8368	15.236	.00000	.8499
x5	1.9375	.8368	2.315	.02568	.1156
x2	-8.1912	1.0481	-7.816	.00000	.5984
x5s	-3.1078	1.0481	-2.965	.00502	.1766
CONSTANT	55.8431				

STD. ERROR OF EST. = 3.3473

ADJUSTED R SQUARED = .8688
R SQUARED = .8804
MULTIPLE R = .9383

ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F RATIO	PROB.
REGRESSION	3382.2833	4	845.5708	75.470	.000E+00
RESIDUAL	459.3689	41	11.2041		
LACK OF FIT	234.5356	36	6.5149	0.145	
PURE ERROR	224.8333	5	44.9667		
TOTAL	3841.6522	45			

------------------ REGRESSION ANALYSIS --------------------

HEADER DATA FOR: C:PAC   LABEL:
NUMBER OF CASES: 46   NUMBER OF VARIABLES: 16

PACIFIC RESUPPLY (Y3) REGRESSION

INDEX	NAME	MEAN	STD. DEV.
1	x2	.0000	.5963
DEP. VAR.:	resup	98.3043	24.4766

DEPENDENT VARIABLE: Y3

VAR.	REGRESS COEFF	STD. ERROR	T(DF= 44)	PROB.
x2	38.2500	2.2458	17.032	.00000
CONSTANT	98.3043			

STD. ERROR OF EST. = 8.9832

r SQUARED = .8683
r = .9318

ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F RATIO	PROB.
REGRESSION	23409.0000	1	23409.0000	290.079	.000E+00
RESIDUAL	3550.7391	44	80.6986		
LACK OF FIT	1976.7361	39	50.6855	0.161	
PURE ERROR	1574.0000	5	314.8000		
TOTAL	26959.7391	45			

------------------------ REGRESSION ANALYSIS ------------------------

HEADER DATA FOR: C:PAC LABEL:
NUMBER OF CASES: 46 NUMBER OF VARIABLES: 16

PACIFIC RESCUE (Y4) REGRESSION

INDEX	NAME	MEAN	STD.DEV.
1	x2	.0000	.5963
2	x5	3.39130E-15	.5963
3	x2s	.3478	.4815
4	x5s	.3478	.4815
DEP. VAR.:	rescu	258.9565	29.2984

DEPENDENT VARIABLE: RESCUE

VAR.	REGRESS COEFF	STD. ERROR	T(DF=41)	PROB.	PARTIAL r^2
x2	46.6250	1.7146	27.193	.00000	.9475
x5	-3.8750	1.7146	-2.260	.02920	.1108
x2s	-11.3922	2.1475	-5.305	.00000	.4070
x5s	4.1078	2.1475	1.913	.06277	.0819
CONSTANT	261.4902				

STD. ERROR OF EST. = 6.8585

ADJUSTED R SQUARED = .9452
R SQUARED = .9501
MULTIPLE R = .9747

ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F RATIO	PROB.
REGRESSION	36699.3150	4	9174.8288	195.047	.000E+00
RESIDUAL	1928.5980	41	47.0390		
LACK OF FIT	1171.098	36	32.5305	0.215	
PURE ERROR	757.5000	5	151.5000		
TOTAL	38627.9130	45			

---------------------- REGRESSION ANALYSIS ----------------------

HEADER DATA FOR: C:PAC LABEL:
NUMBER OF CASES: 46 NUMBER OF VARIABLES: 16

PACIFIC REFUELING (Y5) REGRESSION

INDEX	NAME	MEAN	STD.DEV.
1	x2	.0000	.5963
2	x5	3.39130E-15	.5963
3	x2s	.3478	.4815
4	x5s	.3478	.4815
DEP. VAR.:	refue	227.7826	59.8405

DEPENDENT VARIABLE: REFUEL

VAR.	REGRESS COEFF	STD. ERROR	T(DF=41)	PROB.	PARTIAL r^2
x2	94.4375	3.3914	27.847	.00000	.9498
x5	13.0625	3.3914	3.852	.00040	.2657
x2s	-27.3382	4.2475	-6.436	.00000	.5026
x5s	-11.3382	4.2475	-2.669	.01084	.1481
CONSTANT	241.2353				

STD. ERROR OF EST. = 13.5654

ADJUSTED R SQUARED = .9486
R SQUARED = .9532
MULTIPLE R = .9763

ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F RATIO	PROB.
REGRESSION	153594.9805	4	38398.7451	208.665	.000E+00
RESIDUAL	7544.8456	41	184.0206		
TOTAL	161139.8261	45			

-------------------- REGRESSION ANALYSIS --------------------

HEADER DATA FOR: C:CENT   LABEL:
NUMBER OF CASES: 46   NUMBER OF VARIABLES: 16

CENTCOM INFILTRATION (Y1) REGRESSION

INDEX	NAME	MEAN	STD.DEV.
1	X1	1.69565E-15	.5963
2	x1s	.3478	.4815
DEP. VAR.:	INFIL	143.9348	17.2658

DEPENDENT VARIABLE: INFIL

VAR.	REGRESS COEFF	STD. ERROR	T(DF=43)	PROB.	PARTIAL r^2
X1	21.3750	1.2534	17.054	.00000	.8712
x1s	-21.9417	1.5521	-14.137	.00000	.8229
CONSTANT	151.5667				

STD. ERROR OF EST. = 5.0136

ADJUSTED R SQUARED = .9157
R SQUARED = .9194
MULTIPLE R = .9589

ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQ	F RATIO	PROB.
REGRESSION	12333.9377	2	6166.9688	245.340	.000E+00
RESIDUAL	1080.8667	43	25.1364		
LACK FIT	105.5334	38	2.7772	0.014	
PURE ERR	975.3333	5	195.0667		
TOTAL	13414.8043	45			

---------------------- REGRESSION ANALYSIS ----------------------

HEADER DATA FOR: C:CENT LABEL:
NUMBER OF CASES: 46 NUMBER OF VARIABLES: 16

CENTCOM EXFILTRATION (Y2) REGRESSION

INDEX	NAME	MEAN	STD.DEV.
1	X1	1.69565E-15	.5963
2	x1s	.3478	.4815
DEP. VAR.:	EXFIL	123.7391	29.8875

DEPENDENT VARIABLE: EXFILS

VAR.	REGRESS COEFF	STD. ERROR	T(DF=43)	PROB.	PARTIAL r^2
X1	37.0000	2.1827	16.951	.00000	.8698
x1s	-37.9333	2.7028	-14.035	.00000	.8208
CONSTANT	136.9333				

STD. ERROR OF EST. = 8.7309

ADJUSTED R SQUARED = .9147
R SQUARED = .9185
MULTIPLE R = .9584

ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F RATIO	PROB.
REGRESSION	36919.0029	2	18459.5014	242.157	.000E+00
RESIDUAL	3277.8667	43	76.2295		
LACK FIT	401.0334	38	10.5535	0.018	
PURE ERR	2876.8333	5	575.3667		
TOTAL	40196.8696	45			

---------------------- REGRESSION ANALYSIS ----------------------

HEADER DATA FOR: A:CENT   LABEL:
NUMBER OF CASES: 46   NUMBER OF VARIABLES: 16

CENTCOM RESUPPLY (Y3) REGRESSION

INDEX	NAME	MEAN	STD.DEV.
1	X1	1.69565E-15	.5963
2	X3	7.60870E-16	.5963
3	x1s	.3478	.4815
DEP. VAR.:	RESUPPLY	11.6304	22.7277

DEPENDENT VARIABLE: RESUPPLY

VAR.	REGRESS COEFF	STD. ERROR	T(DF=42)	PROB.	PARTIAL r^2
X1	-29.9375	.6881	-43.508	.00000	.9783
X3	-2.9375	.6881	-4.269	.00011	.3026
x1s	28.4542	.8521	33.395	.00000	.9637
CONSTANT	1.7333				

STD. ERROR OF EST. = 2.7524

ADJUSTED R SQUARED = .9853
R SQUARED = .9863
MULTIPLE R = .9931

ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQ	F RATIO	PROB.
REGRESSION	22926.5382	3	7642.1794	1008.776	.000E+00
RESIDUAL	318.1792	42	7.5757		
LACK FIT	307.3459	37	8.3066	3.834	
PURE ERR	10.8333	5	2.1667		
TOTAL	23244.7174	45			

REGRESSION ANALYSIS

HEADER DATA FOR: B:CENT LABEL:
NUMBER OF CASES: 46 NUMBER OF VARIABLES: 16

CENTCOM RESCUE (Y4) REGRESSION

INDEX	NAME	MEAN	STD.DEV.
1	X1	1.69565E-15	.5963
2	x1s	.3478	.4815
DEP. VAR.:	RESCUE	69.3043	18.9196

DEPENDENT VARIABLE: RESCUE

VAR.	REGRESS COEFF	STD. ERROR	T(DF=43)	PROB.	PARTIAL r^2
X1	24.0625	.7352	32.731	.00000	.9614
x1s	-24.9042	.9103	-27.357	.00000	.9457
CONSTANT	77.9667				

STD. ERROR OF EST. = 2.9407

ADJUSTED R SQUARED = .9758
R SQUARED = .9769
MULTIPLE R = .9884

ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQ	F RATIO	PROB.
REGRESSION	15735.8975	2	7867.9487	909.854	.000E+00
RESIDUAL	371.8417	43	8.6475		
LACK FIT	133.0084	38	3.5002	0.073	
PURE ERR	238.8333	5	47.7667		
TOTAL	16107.7391	45			

---------------------- REGRESSION ANALYSIS ----------------------

HEADER DATA FOR: B:CENT   LABEL:
NUMBER OF CASES: 46   NUMBER OF VARIABLES: 16

CENTCOM REFUELING (Y5) REGRESSION

INDEX	NAME	MEAN	STD.DEV.
1	X1	1.69565E-15	.5963
2	x1s	.3478	.4815
DEP. VAR.:	REFUEL	248.7174	51.3717

DEPENDENT VARIABLE: REFUEL

VAR.	REGRESS COEFF	STD. ERROR	T(DF=43)	PROB.	PARTIAL r^2
X1	64.1250	3.1617	20.282	.00000	.9054
x1s	-66.4583	3.9151	-16.975	.00000	.8701
CONSTANT	271.8333				

STD. ERROR OF EST. = 12.6470

ADJUSTED R SQUARED = .9394
R SQUARED = .9421
MULTIPLE R = .9706

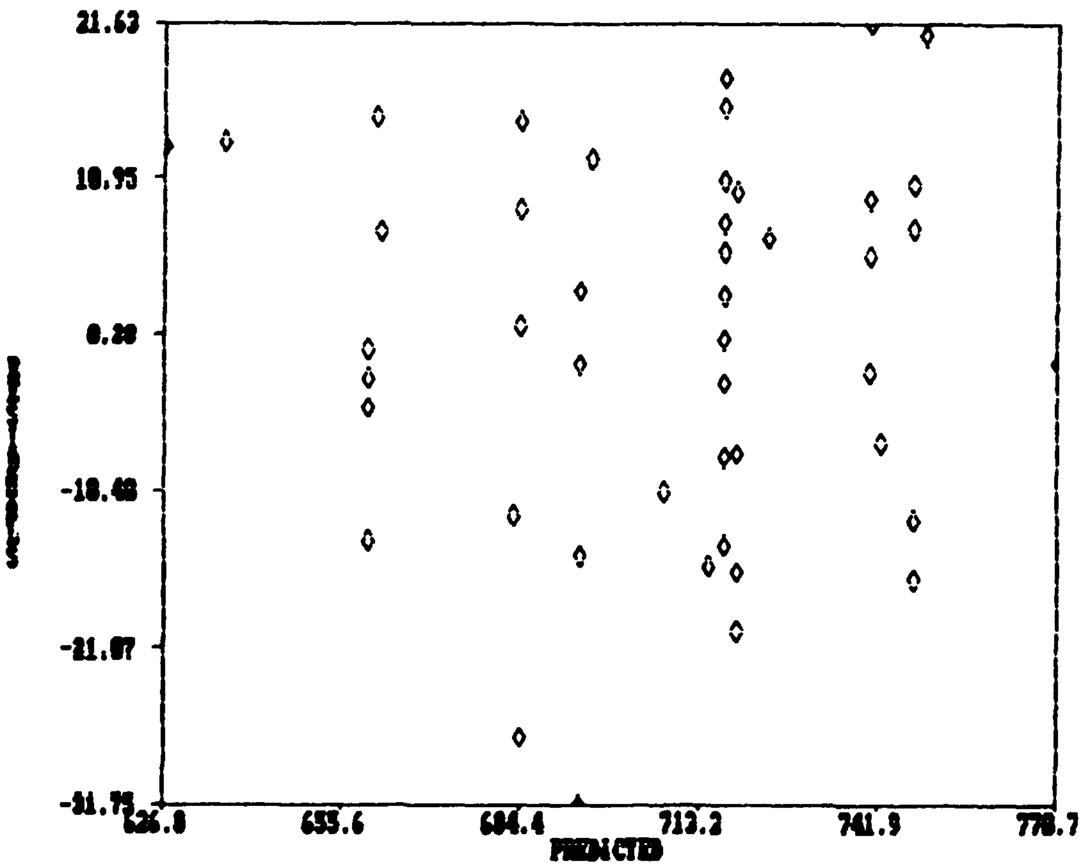
ANALYSIS OF VARIANCE TABLE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQ	F RATIO	PROB.
REGRESSION	111879.6594	2	55939.8297	349.743	.000E+00
RESIDUAL	6877.6667	43	159.9457		
LACK FIT	552.8334	38	14.5482	0.012	
PURE ERR	6324.8333	5	1264.9667		
TOTAL	118757.3261	45			

APPENDIX D: Europe Infil Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	655	659.766	-4.7660	24	650	636.453	13.5470
2	657	659.766	-2.7660	25	731	724.078	6.9220
3	758	747.391	10.6090	26	671	683.078	-12.0780
4	755	747.391	7.6090	27	769	770.703	-1.7030
5	679	693.746	-14.7460	28	717	717.059	-0.0590
6	762	740.371	21.6290	29	728	717.059	10.9410
7	662	693.746	-31.7460	30	714	717.059	-3.0590
8	738	740.371	-2.3710	31	723	717.059	5.9410
9	640	626.827	13.1730	32	676	660.808	15.1920
10	699	714.452	-15.4520	33	697	707.433	-10.4330
11	669	661.577	7.4230	34	708	695.558	12.4420
12	770	749.202	20.7980	35	735	742.183	-7.1830
13	692	693.746	-1.7460	36	685	684.12	0.8800
14	697	693.746	3.2540	37	657	684.12	-27.1200
15	750	740.371	9.6290	38	703	718.87	-15.8700
16	746	740.371	5.6290	39	699	718.87	-19.8700
17	693	684.12	8.8800	40	646	659.766	-13.7660
18	699	684.12	14.8800	41	735	747.391	-12.3910
19	711	718.87	-7.8700	42	659	659.766	-0.7660
20	729	718.87	10.1300	43	731	747.391	-16.3910
21	709	717.059	-8.0590	44	725	717.059	7.9410
22	703	717.059	-14.0590	45	735	717.059	17.9410
23	720	717.059	2.9410	46	733	717.059	15.9410

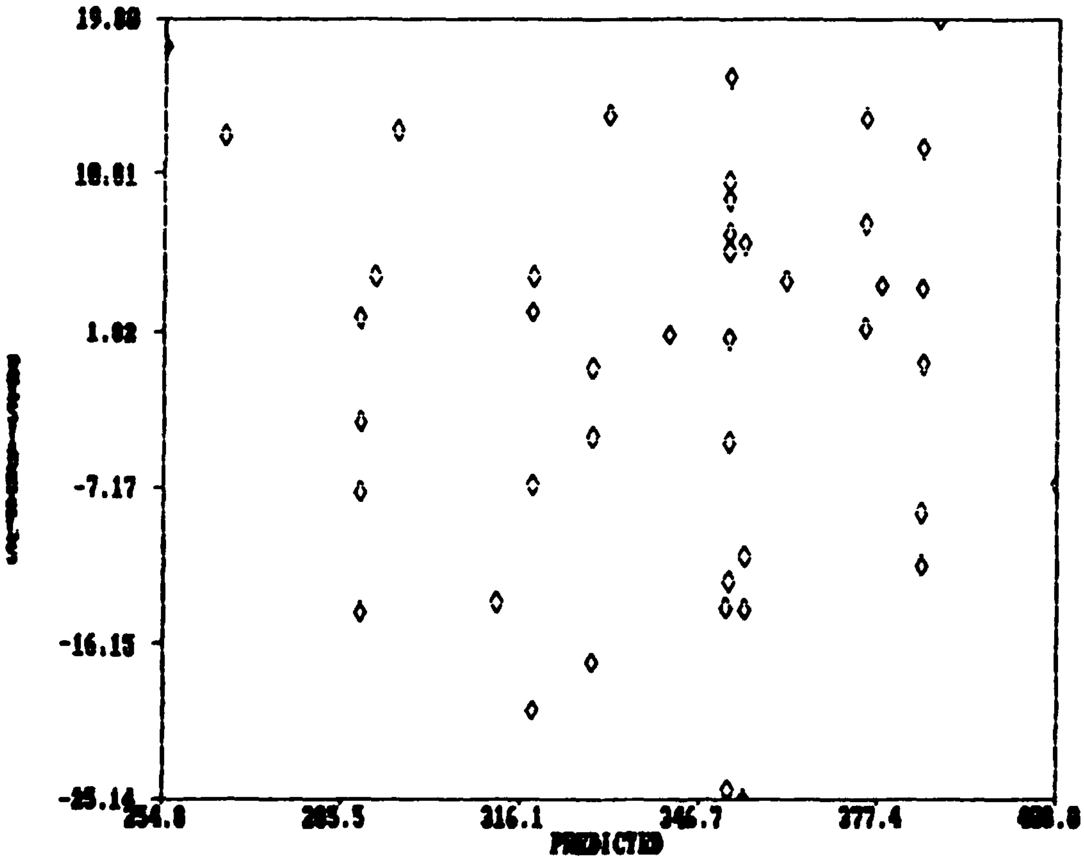
EUROPE INFIL RESIDUAL PLOT



Europe Exfil Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	291	288.37	2.6300	24	278	264.995	13.0050
2	285	288.37	-3.3700	25	366	361.245	4.7550
3	397	384.62	12.3800	26	298	311.745	-13.7450
4	389	384.62	4.3800	27	401	407.995	-6.9950
5	311	328.184	-17.1840	28	362	351.559	10.4410
6	389	374.934	14.0660	29	368	351.559	16.4410
7	328	328.184	-0.1840	30	358	351.559	6.4410
8	377	374.934	2.0660	31	359	351.559	7.4410
9	273	254.827	18.1730	32	308	294.641	13.3590
10	337	351.077	-14.0770	33	343	341.391	1.6090
11	296	290.952	5.0480	34	345	330.766	14.2340
12	407	387.202	19.7980	35	382	377.516	4.4840
13	324	328.184	-4.1840	36	311	318.016	-7.0160
14	324	328.184	-4.1840	37	298	318.016	-20.0160
15	383	374.934	8.0660	38	340	354.141	-14.1410
16	385	384.934	0.0660	39	329	354.141	-25.1410
17	323	318.016	4.9840	40	274	288.37	-14.3700
18	321	318.016	2.9840	41	376	384.62	-8.6200
19	343	354.141	-11.1410	42	281	288.37	-7.3700
20	361	354.141	6.8590	43	373	384.62	-11.6200
21	347	351.559	-4.5590	44	353	351.559	1.4410
22	327	351.559	-24.5590	45	361	351.559	9.4410
23	339	351.559	-12.5590	46	362	351.559	10.441

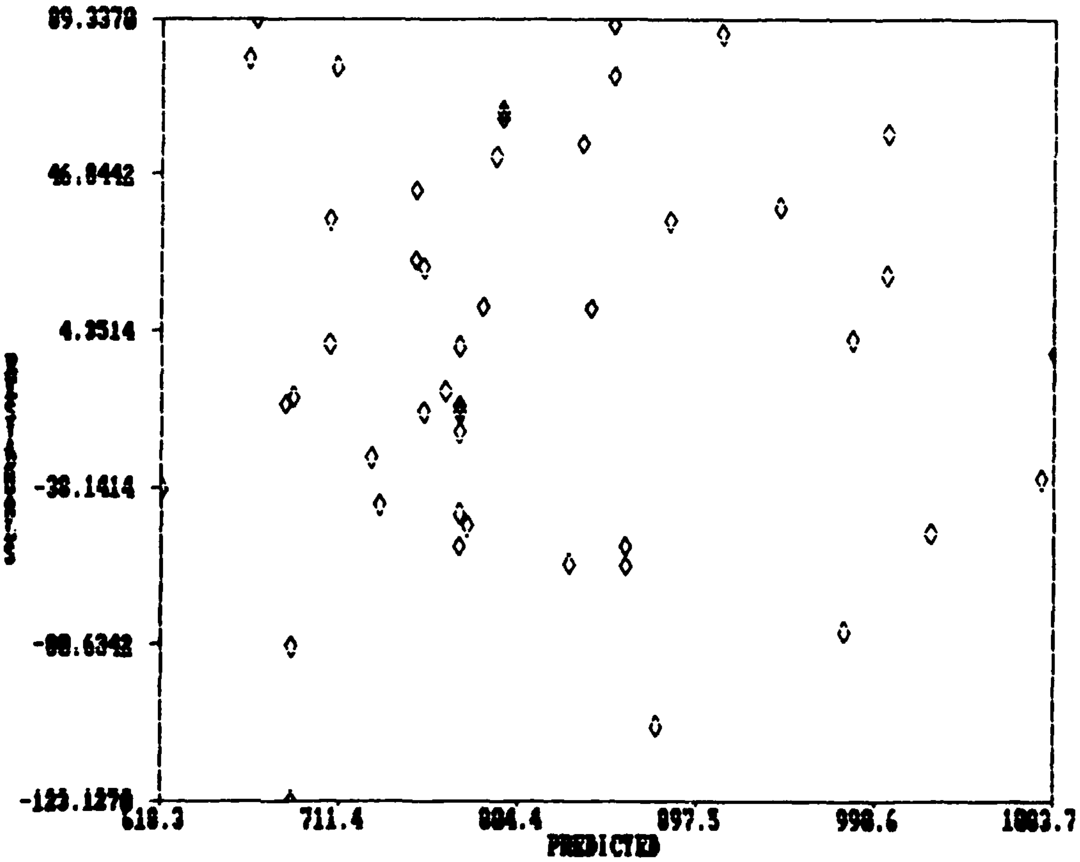
EUROPE EXFIL RESIDUAL PLOT



Europe Resupply Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	785	708.752	76.2480	24	580	618.288	-38.2880
2	742	663.502	78.4980	25	844	792.288	51.7120
3	917	882.752	34.2480	26	995	909.663	85.3370
4	893	837.502	55.4980	27	1082	1083.663	-1.6630
5	740	705.288	34.7120	28	858	795.752	62.2480
6	1016	996.663	19.3370	29	774	750.502	23.4980
7	706	705.288	0.7120	30	860	795.752	64.2480
8	1055	996.663	58.3370	31	793	750.502	42.4980
9	754	766.288	-12.2880	32	796	785.449	10.5510
10	978	940.288	37.7120	33	1041	1076.824	-35.8240
11	757	667.663	89.3370	34	673	686.824	-13.8240
12	852	841.663	10.3370	35	980	978.199	1.8010
13	698	727.913	-29.9130	36	773	875.913	-102.9130
14	667	682.663	-15.6630	37	772	830.663	-58.6630
15	969	1019.288	-50.2880	38	729	777.288	-48.2880
16	897	974.038	-77.0380	39	689	732.038	-43.0380
17	927	853.288	73.7120	40	563	686.127	-123.1270
18	941	853.288	87.7120	41	806	860.127	-54.1270
19	776	754.663	21.3370	42	605	686.127	-81.1270
20	737	754.663	-17.6630	43	801	860.127	-59.1270
21	757	773.127	-16.1270	44	750	773.127	-23.1270
22	728	773.127	-45.1270	45	755	773.127	-18.1270
23	719	773.127	-54.1270	46	773	773.127	-0.12699999

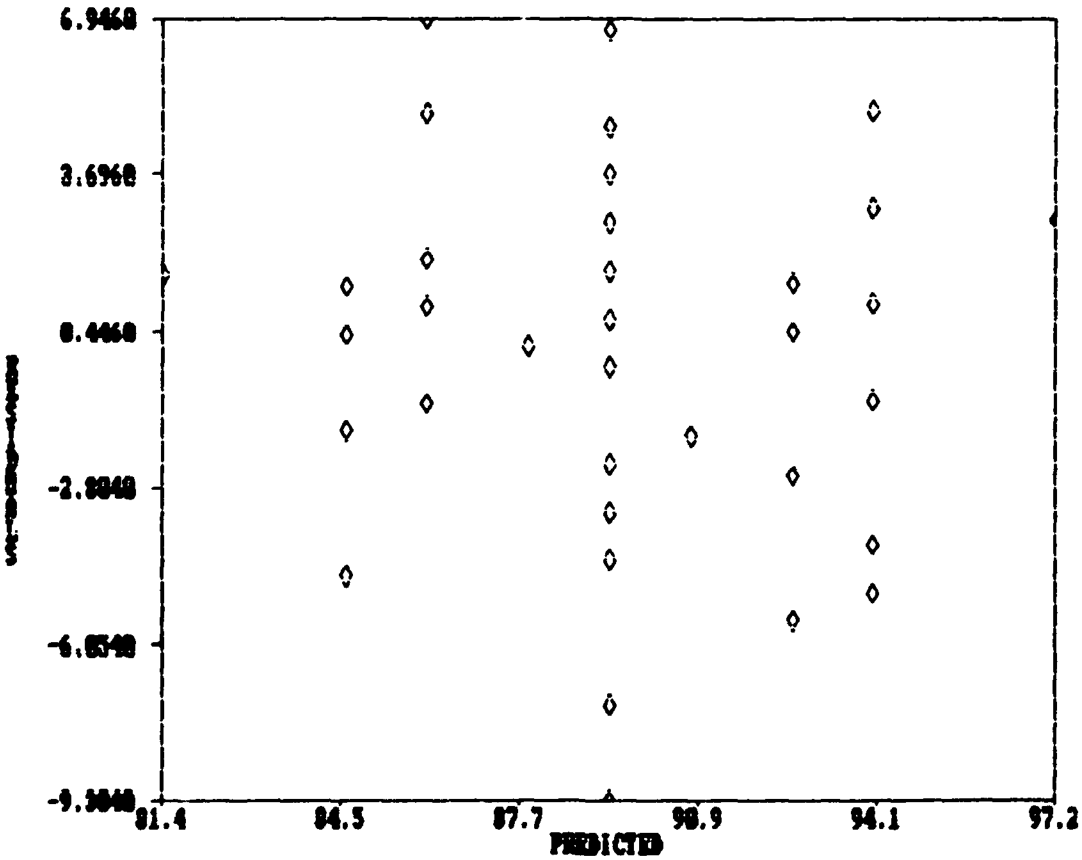
EUROPE RESUPPLY RESIDUAL PLOT



Europe Rescue Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	86	84.617	1.3830	24	83	81.367	1.6330
2	86	84.617	1.3830	25	89	90.742	-1.7420
3	95	93.992	1.0080	26	88	87.867	0.1330
4	95	93.992	1.0080	27	100	97.242	2.7580
5	93	93.992	-0.9920	28	91	89.304	1.6960
6	91	86.054	4.9460	29	90	89.304	0.6960
7	87	86.054	0.9460	30	90	89.304	0.6960
8	90	92.554	-2.5540	31	93	89.304	3.6960
9	86	84.617	1.3830	32	87	86.054	0.9460
10	99	93.992	5.0080	33	93	92.554	0.4460
11	85	84.617	0.3830	34	93	86.054	6.9460
12	97	93.992	3.0080	35	87	92.554	-5.5540
13	85	86.054	-1.0540	36	96	89.304	6.6960
14	88	86.054	1.9460	37	91	89.304	1.6960
15	94	92.554	1.4460	38	85	89.304	-4.3040
16	93	92.554	0.4460	39	87	89.304	-2.3040
17	93	89.304	3.6960	40	83	84.617	-1.6170
18	89	89.304	-0.3040	41	90	93.992	-3.9920
19	90	89.304	0.6960	42	80	84.617	-4.6170
20	91	89.304	1.6960	43	89	93.992	-4.9920
21	92	89.304	2.6960	44	82	89.304	-7.3040
22	86	89.304	-3.3040	45	91	89.304	1.6960
23	80	89.304	-9.3040	46	94	89.304	4.6960

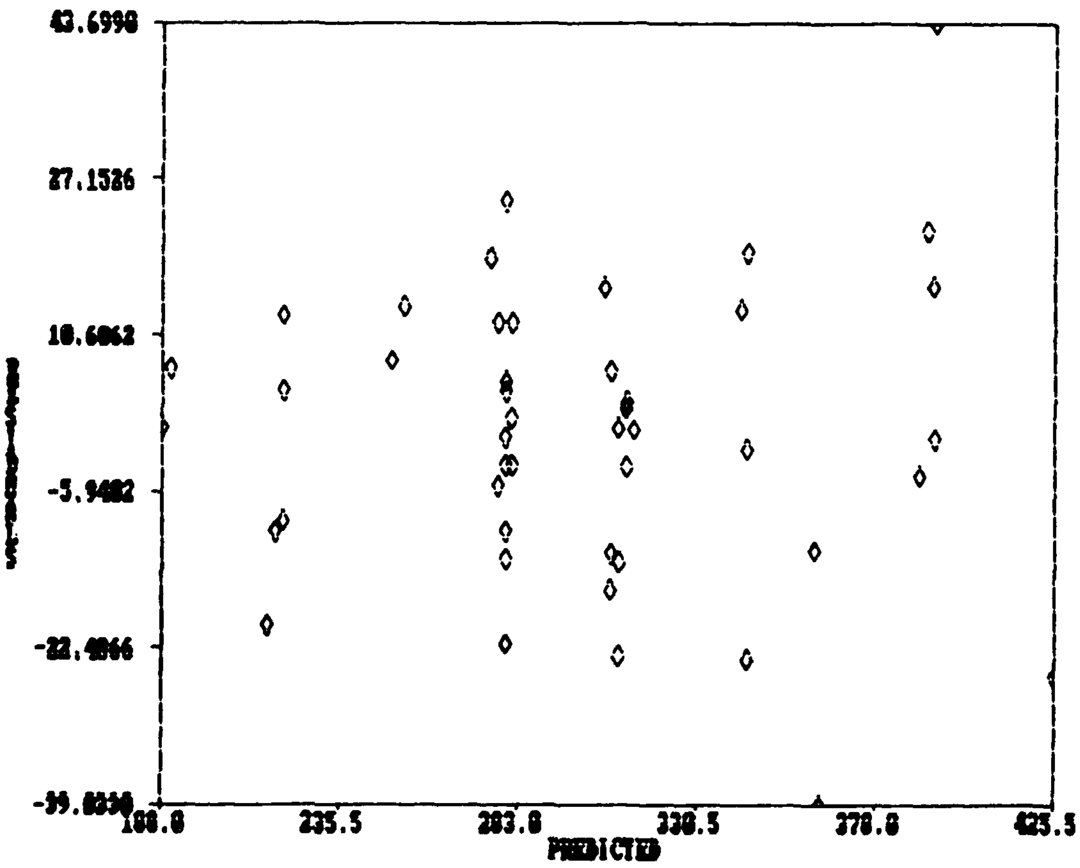
EUROPE RESCUE RESIDUAL PLOT



Europe Refueling Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	266	252.384	13.6160	24	211	220.033	-9.0330
2	196	216.134	-20.1340	25	409	393.158	15.8420
3	400	425.509	-25.5090	26	189	188.033	0.9670
4	385	389.259	-4.2590	27	349	361.158	-12.1580
5	308	311.262	-3.2620	28	320	343.613	-23.6130
6	285	279.262	5.7380	29	291	307.363	-16.3630
7	314	311.262	2.7380	30	363	343.613	19.3870
8	284	279.262	4.7380	31	295	307.363	-12.3630
9	197	189.908	7.0920	32	293	280.994	12.0060
10	324	363.033	-39.0330	33	257	248.994	8.0060
11	208	218.158	-10.1580	34	310	309.244	0.7560
12	413	391.283	21.7170	35	272	277.244	-5.2440
13	342	343.47	-1.4700	36	314	313.345	0.6550
14	314	307.22	6.7800	37	289	277.095	11.9050
15	315	311.47	3.5300	38	355	341.595	13.4050
16	294	275.22	18.7800	39	321	305.345	15.6550
17	283	281.137	1.8630	40	225	220.176	4.8240
18	278	281.137	-3.1370	41	437	393.301	43.6990
19	286	309.387	-23.3870	42	233	220.176	12.8240
20	296	309.387	-13.3870	43	393	393.301	-0.3010
21	304	279.119	24.8810	44	279	27c 119	-0.1190
22	257	279.119	-22.1190	45	269	279.119	-10.1190
23	266	279.119	-13.1190	46	276	279.119	-3.1190

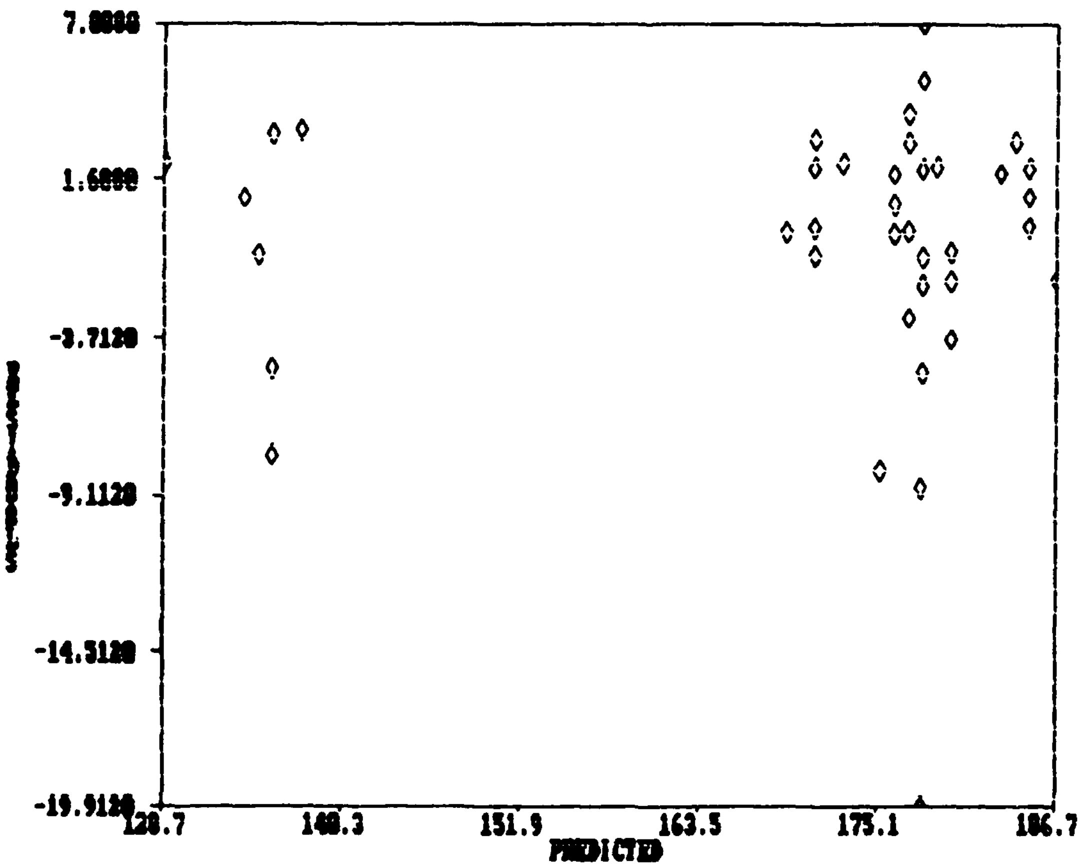
EUROPE REFUELING RESIDUAL PLOT



Pacific Infil Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	131	135.737	-4.7370	24	135	133.924	1.0760
2	128	135.737	-7.7370	25	185	183.049	1.9510
3	185	184.862	0.1380	26	141	137.549	3.4510
4	187	184.862	2.1380	27	185	186.674	-1.6740
5	178	176.099	1.9010	28	180	177.912	2.0880
6	176	179.724	-3.7240	29	176	177.912	-1.9120
7	177	176.099	0.9010	30	185	177.912	7.0880
8	178	179.724	-1.7240	31	177	177.912	-0.9120
9	131	128.728	2.2720	32	169	169.091	-0.0910
10	169	177.853	-8.8530	33	175	172.716	2.2840
11	134	134.853	-0.8530	34	167	175.216	-8.2160
12	187	183.978	3.0220	35	181	178.841	2.1590
13	176	176.099	-0.0990	36	170	170.903	-0.9030
14	178	176.099	1.9010	37	173	170.903	2.0970
15	179	179.724	-0.7240	38	180	177.028	2.9720
16	179	179.724	-0.7240	39	181	177.028	3.9720
17	174	170.903	3.0970	40	139	135.737	3.2630
18	171	170.903	0.0970	41	187	184.862	2.1380
19	177	177.028	-0.0280	42	139	135.737	3.2630
20	174	177.028	-3.0280	43	186	184.862	1.1380
21	173	177.912	-4.9120	44	183	177.912	5.0880
22	158	177.912	-19.9120	45	180	177.912	2.0880
23	180	177.912	2.0880	46	185	177.912	7.0880

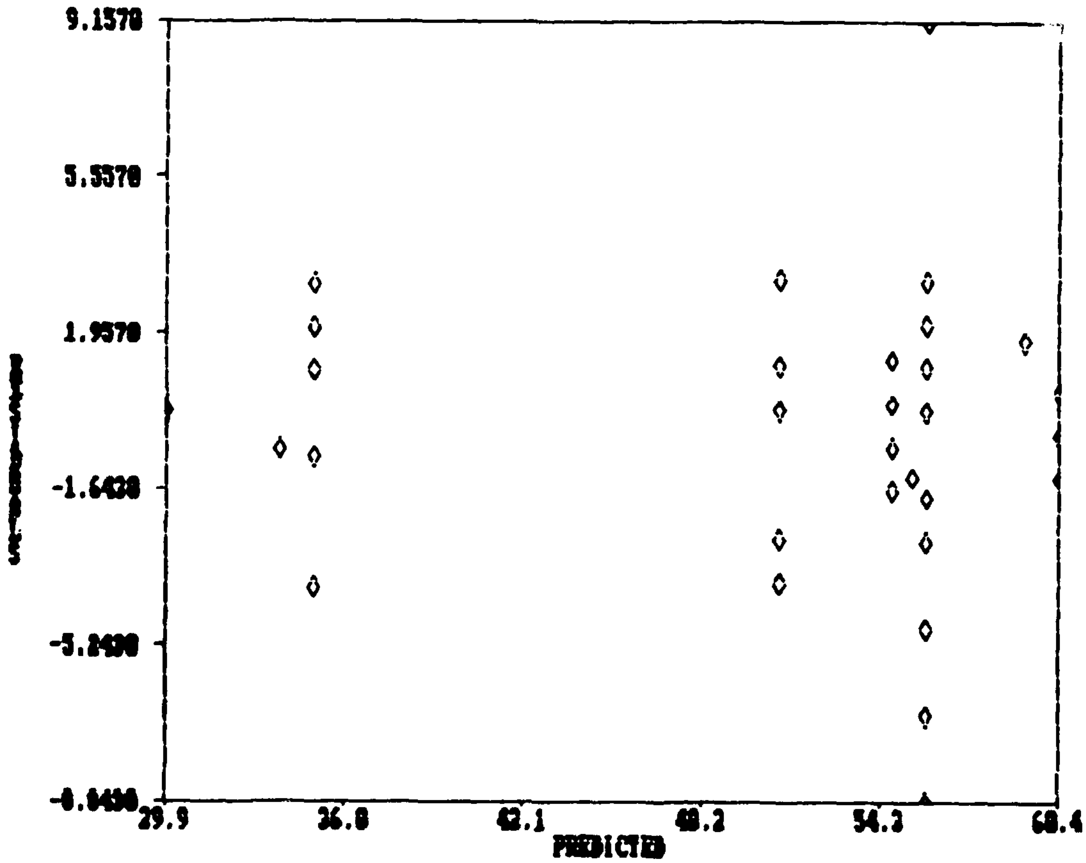
PACIFIC INFIL RESIDUAL PLOT



Pacific Exfil Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	37	34.902	2.0980	24	36	34.902	1.0980
2	34	34.902	-0.9020	25	61	60.402	0.5980
3	61	60.402	0.5980	26	31	34.902	-3.9020
4	60	60.402	-0.4020	27	60	60.402	-0.4020
5	57	55.843	1.1570	28	49	55.843	-6.8430
6	56	55.843	0.1570	29	51	55.843	-4.8430
7	57	55.843	1.1570	30	53	55.843	-2.8430
8	58	55.843	2.1570	31	57	55.843	1.1570
9	30	29.857	0.1430	32	51	50.798	0.2020
10	54	55.357	-1.3570	33	48	50.798	-2.7980
11	33	33.732	-0.7320	34	53	54.673	-1.6730
12	61	59.232	1.7680	35	54	54.673	-0.6730
13	53	55.843	-2.8430	36	54	50.798	3.2020
14	54	55.843	-1.8430	37	54	50.798	3.2020
15	53	55.843	-2.8430	38	55	54.673	0.3270
16	58	55.843	2.1570	39	56	54.673	1.3270
17	47	50.798	-3.7980	40	38	34.902	3.0980
18	52	50.798	1.2020	41	61	60.402	0.5980
19	55	54.673	0.3270	42	34	34.902	-0.9020
20	54	54.673	-0.6730	43	59	60.402	-1.4020
21	56	55.843	0.1570	44	57	55.843	1.1570
22	47	55.843	-8.8430	45	59	55.843	3.1570
23	65	55.843	9.1570	46	65	55.843	9.1570

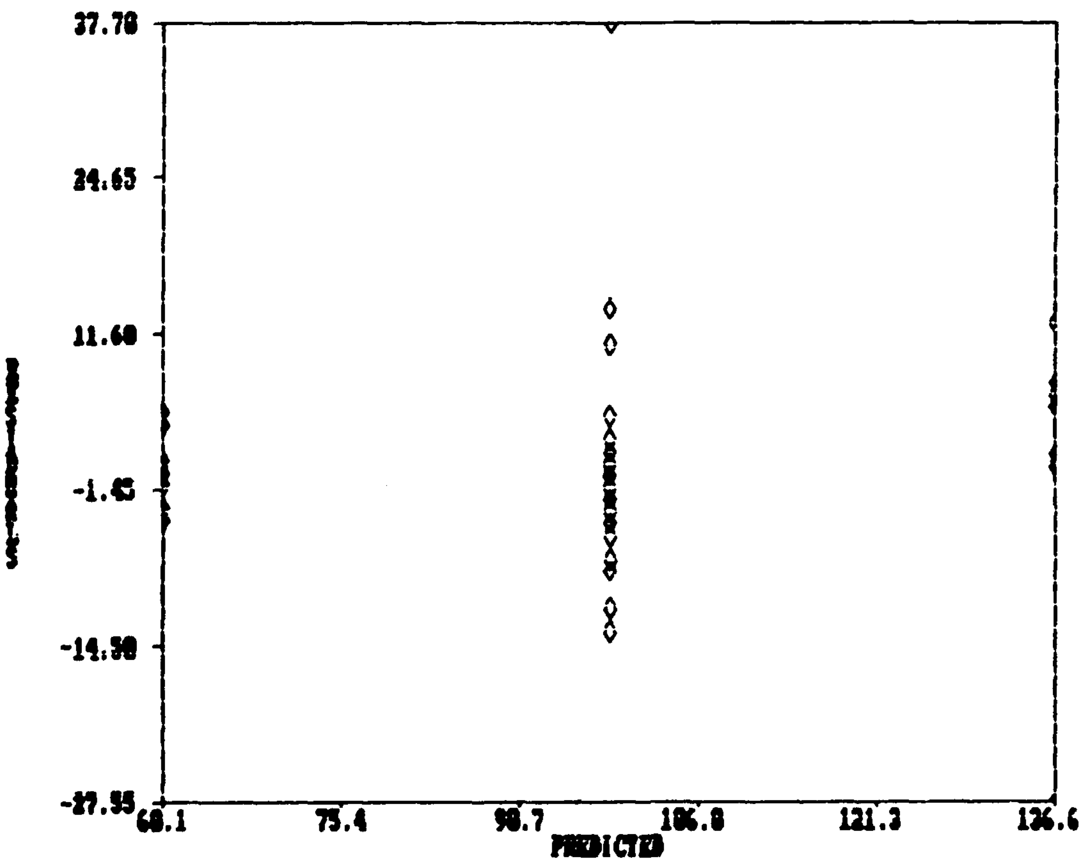
PACIFIC EXFIL RESIDUAL PLOT



Pacific Resupply Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	56	60.054	-4.0540	24	64	60.054	3.9460
2	65	60.054	4.9460	25	137	136.554	0.4460
3	142	136.554	5.4460	26	60	60.054	-0.0540
4	149	136.554	12.4460	27	137	136.554	0.4460
5	97	98.304	-1.3040	28	97	98.304	-1.3040
6	94	98.304	-4.3040	29	97	98.304	-1.3040
7	97	98.304	-1.3040	30	90	98.304	-8.3040
8	95	98.304	-3.3040	31	98	98.304	-0.3040
9	65	60.054	4.9460	32	94	98.304	-4.3040
10	109	136.554	-27.5540	33	93	98.304	-5.3040
11	57	60.054	-3.0540	34	91	98.304	-7.3040
12	144	136.554	7.4460	35	96	98.304	-2.3040
13	87	98.304	-11.3040	36	94	98.304	-4.3040
14	101	98.304	2.6960	37	93	98.304	-5.3040
15	99	98.304	0.6960	38	96	98.304	-2.3040
16	95	98.304	-3.3040	39	103	98.304	4.6960
17	109	98.304	10.6960	40	61	60.054	0.9460
18	100	98.304	1.6960	41	138	136.554	1.4460
19	96	98.304	-2.3040	42	59	60.054	-1.0540
20	94	98.304	-4.3040	43	143	136.554	6.4460
21	103	98.304	4.6960	44	101	98.304	2.6960
22	85	98.304	-13.3040	45	136	98.304	37.6960
23	112	98.304	13.6960	46	93	98.304	-5.3040

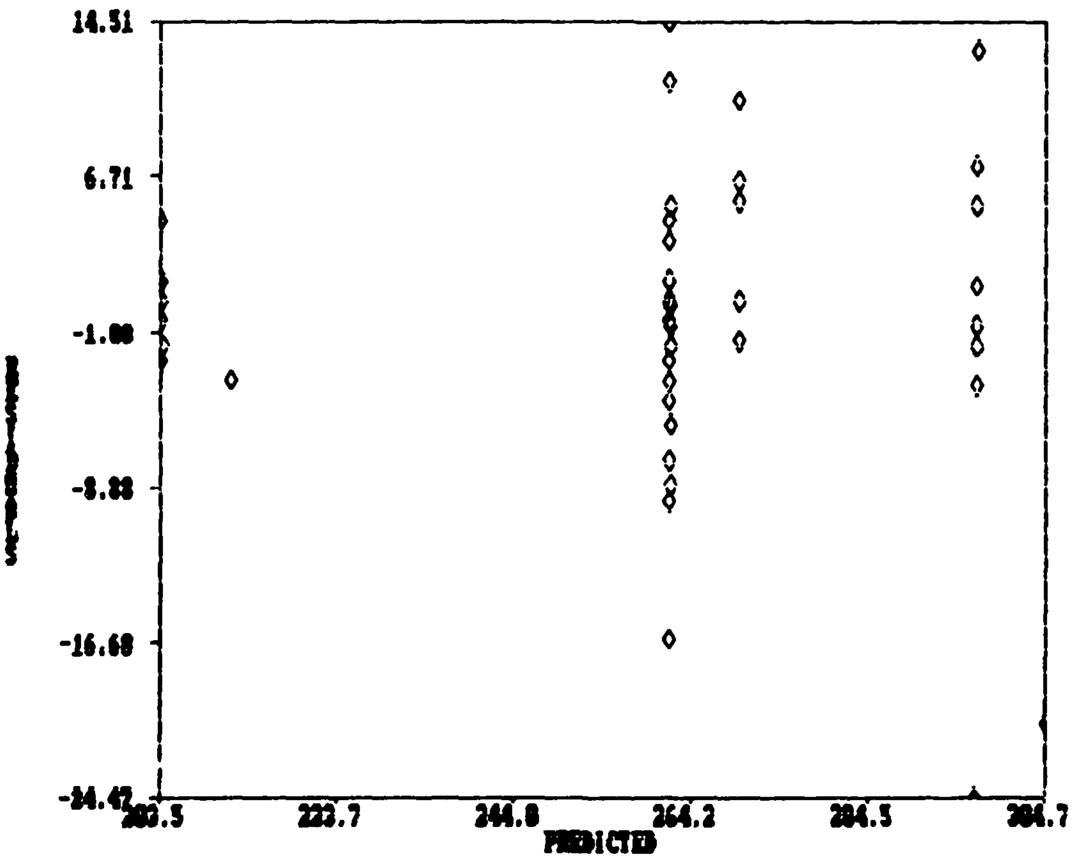
PACIFIC RESUPPLY RESIDUAL PLOT



Pacific Rescue Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	204	203.473	0.5270	24	208	203.473	4.5270
2	203	203.473	-0.4730	25	295	296.723	-1.7230
3	304	296.723	7.2770	26	205	203.473	1.5270
4	298	296.723	1.2770	27	293	296.723	-3.7230
5	261	261.49	-0.4900	28	259	261.49	-2.4900
6	262	261.49	0.5100	29	259	261.49	-2.4900
7	263	261.49	1.5100	30	266	261.49	4.5100
8	261	261.49	-0.4900	31	261	261.49	-0.4900
9	208	211.456	-3.4560	32	268	269.473	-1.4730
10	284	304.706	-20.7060	33	280	269.473	10.5270
11	202	203.706	-1.7060	34	267	261.723	5.2770
12	310	296.956	13.0440	35	260	261.723	-1.7230
13	263	261.49	1.5100	36	270	269.473	0.5270
14	258	261.49	-3.4900	37	272	296.473	-24.4730
15	259	261.49	-2.4900	38	253	261.723	-8.7230
16	265	261.49	3.5100	39	256	261.723	-5.7230
17	275	269.473	5.5270	40	201	203.473	-2.4730
18	276	269.473	6.5270	41	302	296.723	5.2770
19	262	261.723	0.2770	42	205	203.473	1.5270
20	261	261.723	-0.7230	43	296	296.723	-0.7230
21	254	261.49	-7.4900	44	245	261.49	-16.4900
22	276	261.49	14.5100	45	273	261.49	11.5100
23	252	261.49	-9.4900	46	257	261.49	-4.4900

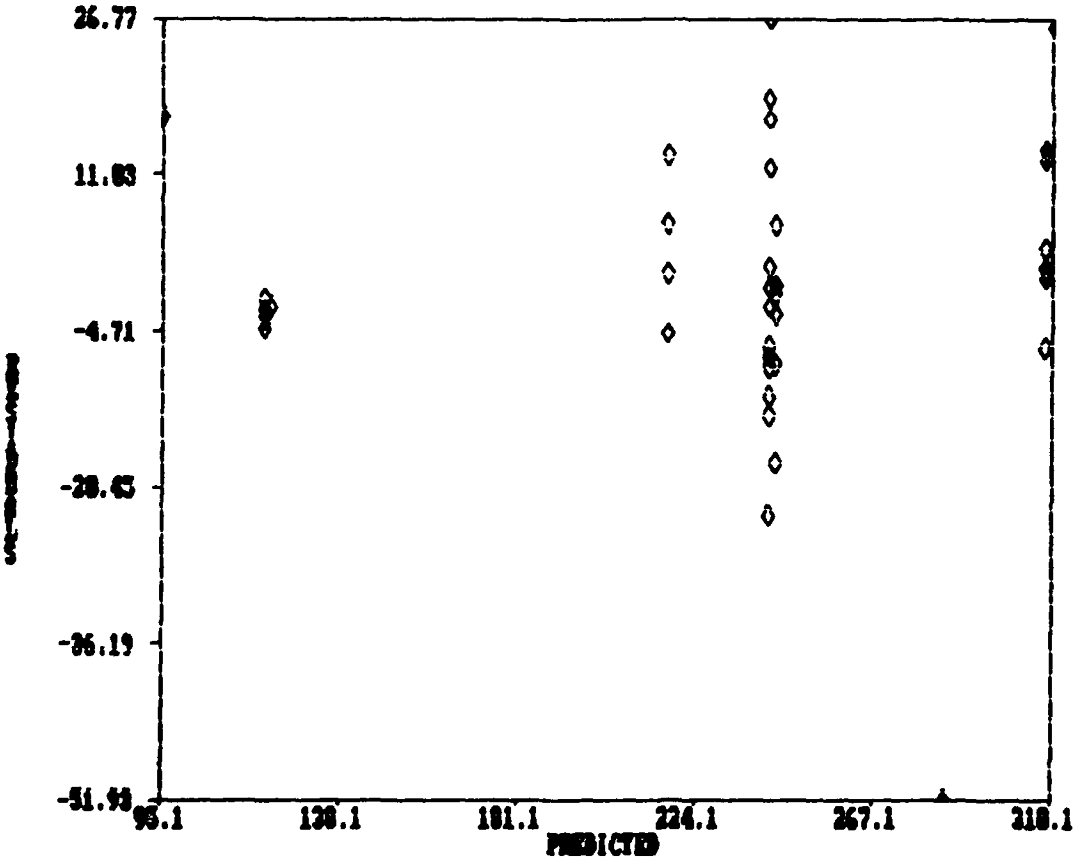
PACIFIC RESCUE RESIDUAL PLOT



Pacific Refueling Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	117	119.46	-2.4600	24	118	119.46	-1.4600
2	115	119.46	-4.4600	25	310	308.335	1.6650
3	321	308.335	12.6650	26	118	119.46	-1.4600
4	322	308.335	13.6650	27	302	308.335	-6.3350
5	243	241.235	1.7650	28	230	241.235	-11.2350
6	239	241.235	-2.2350	29	233	241.235	-8.2350
7	239	241.235	-2.2350	30	235	241.235	-6.2350
8	239	241.235	-2.2350	31	239	241.235	-2.2350
9	112	95.059	16.9410	32	212	216.835	-4.8350
10	232	283.934	-51.9340	33	218	216.835	1.1650
11	119	121.184	-2.1840	34	225	242.96	-17.9600
12	336	310.059	25.9410	35	242	242.96	-0.9600
13	228	241.235	-13.2350	36	230	216.835	13.1650
14	241	241.235	-0.2350	37	230	216.835	13.1650
15	234	241.235	-7.2350	38	243	242.96	0.0400
16	239	241.235	-2.2350	39	249	242.96	6.0400
17	223	216.835	6.1650	40	118	119.46	-1.4600
18	223	216.835	6.1650	41	312	308.335	3.6650
19	240	242.96	-2.9600	42	116	119.46	-3.4600
20	235	242.96	-7.9600	43	309	308.335	0.6650
21	235	241.235	-6.2350	44	268	241.235	26.7650
22	218	241.235	-23.2350	45	258	241.235	16.7650
23	260	241.235	18.7650	46	253	241.235	11.7650

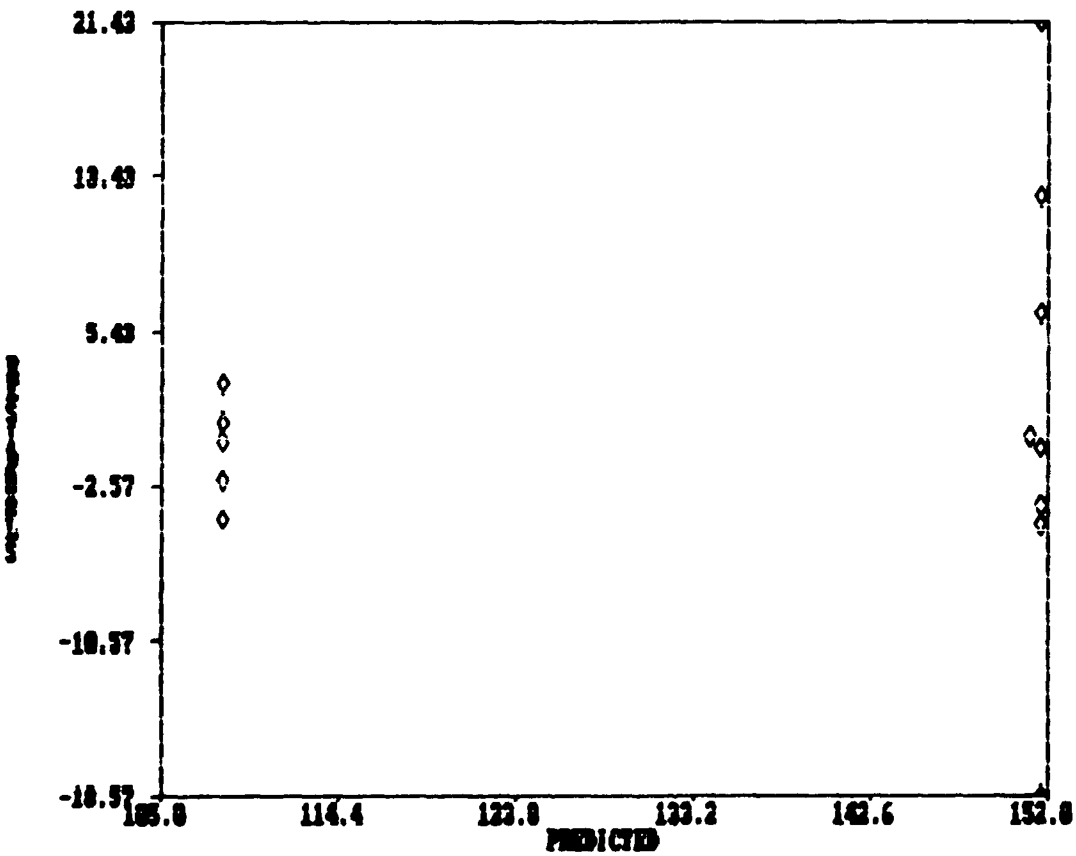
PACIFIC REFUELING RESIDUAL PLOT



Centcom Infil Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	111	108.25	2.7500	24	151	151.567	-0.5670
2	151	151	0.0000	25	151	151.567	-0.5670
3	111	108.25	2.7500	26	151	151.567	-0.5670
4	151	151	0.0000	27	151	151.567	-0.5670
5	151	151.567	-0.5670	28	108	108.25	-0.2500
6	151	151.567	-0.5670	29	151	151	0.0000
7	148	151.567	-3.5670	30	106	108.25	-2.2500
8	151	151.567	-0.5670	31	151	151	0.0000
9	151	151.567	-0.5670	32	151	151.567	-0.5670
10	151	151.567	-0.5670	33	151	151.567	-0.5670
11	151	151.567	-0.5670	34	151	151.567	-0.5670
12	151	151.567	-0.5670	35	151	151.567	-0.5670
13	109	108.25	0.7500	36	108	108.25	-0.2500
14	151	151	0.0000	37	151	151	0.0000
15	109	108.25	0.7500	38	104	108.25	-4.2500
16	151	151	0.0000	39	151	151	0.0000
17	151	151.567	-0.5670	40	151	151.567	-0.5670
18	151	151.567	-0.5670	41	151	151.567	-0.5670
19	151	151.567	-0.5670	42	151	151.567	-0.5670
20	151	151.567	-0.5670	43	151	151.567	-0.5670
21	151	151.567	-0.5670	44	147	151.567	-4.5670
22	158	151.567	6.4330	45	133	151.567	-18.5670
23	164	151.567	12.4330	46	173	151.567	21.4330

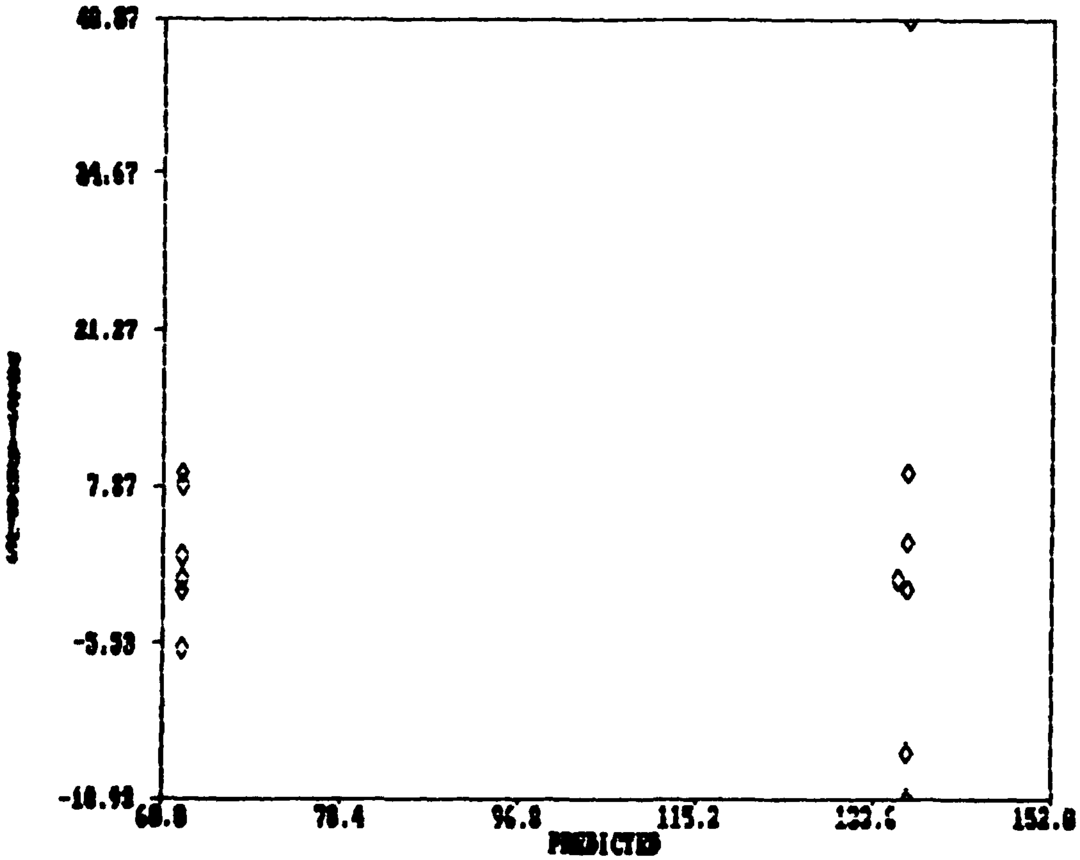
CENTCOM INFIL RESIDUAL PLOT



Centcom Exfil Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	61	62	-1.0000	24	136	136.933	-0.9330
2	136	136	0.0000	25	136	136.933	-0.9330
3	56	62	-6.0000	26	136	136.933	-0.9330
4	136	136	0.0000	27	136	136.933	-0.9330
5	136	136.933	-0.9330	28	62	62	0.0000
6	136	136.933	-0.9330	29	136	136	0.0000
7	136	136.933	-0.9330	30	70	62	8.0000
8	136	136.933	-0.9330	31	136	136	0.0000
9	136	136.933	-0.9330	32	136	136.933	-0.9330
10	136	136.933	-0.9330	33	136	136.933	-0.9330
11	136	136.933	-0.9330	34	136	136.933	-0.9330
12	136	136.933	-0.9330	35	136	136.933	-0.9330
13	64	62	2.0000	36	56	62	-6.0000
14	136	136	0.0000	37	136	136	0.0000
15	56	62	-6.0000	38	71	62	9.0000
16	136	136	0.0000	39	136	136	0.0000
17	136	136.933	-0.9330	40	136	136.933	-0.9330
18	136	136.933	-0.9330	41	136	136.933	-0.9330
19	136	136.933	-0.9330	42	136	136.933	-0.9330
20	136	136.933	-0.9330	43	136	136.933	-0.9330
21	136	136.933	-0.9330	44	122	136.933	-14.9330
22	140	136.933	3.0670	45	118	136.933	-18.9330
23	146	136.933	9.0670	46	185	136.933	48.0670

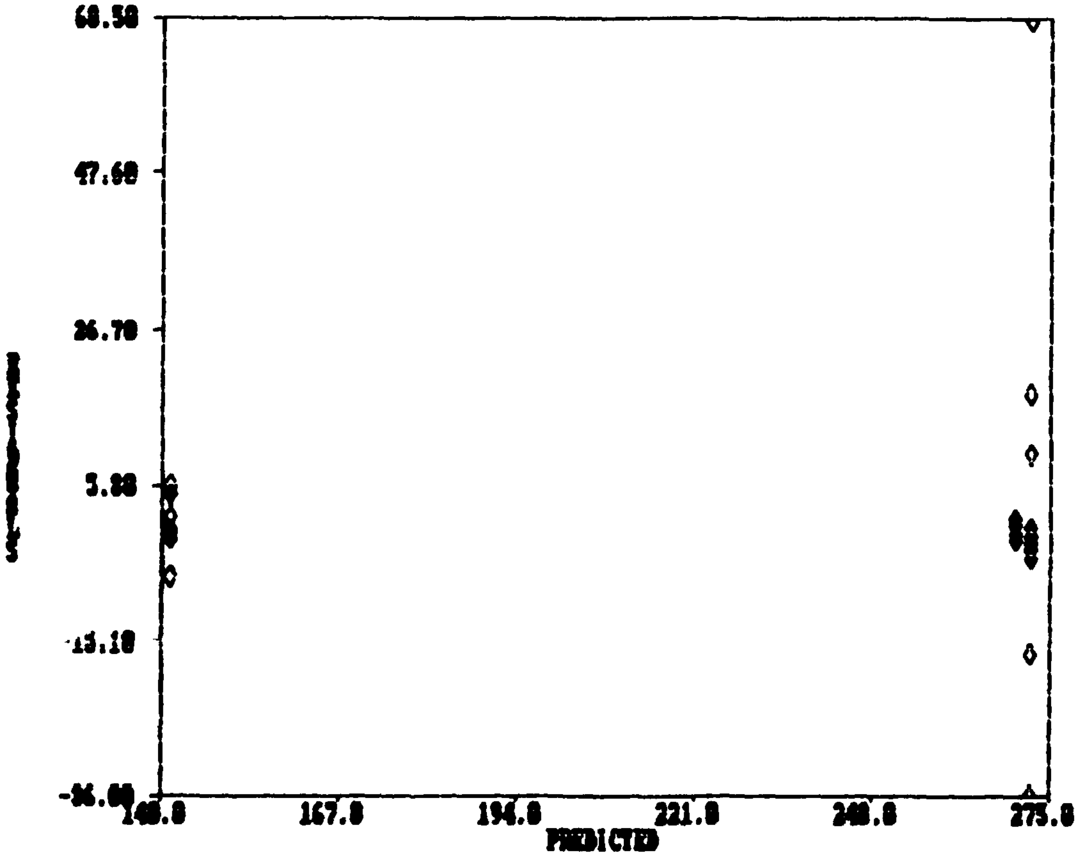
CENTCOM EXFIL RESIDUAL PLOT



Centcom Refueling Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	143	141.25	1.7500	24	271	271.833	-0.8330
2	268	269.5	-1.5000	25	271	271.833	-0.8330
3	140	141.25	-1.2500	26	270	271.833	-1.8330
4	268	269.5	-1.5000	27	270	271.833	-1.8330
5	272	271.833	0.1670	28	141	141.25	-0.2500
6	269	271.833	-2.8330	29	269	269.5	-0.5000
7	268	271.833	-3.8330	30	147	141.25	5.7500
8	270	271.833	-1.8330	31	269	269.5	-0.5000
9	270	271.833	-1.8330	32	270	271.833	-1.8330
10	270	271.833	-1.8330	33	270	271.833	-1.8330
11	269	271.833	-2.8330	34	272	271.833	0.1670
12	269	271.833	-2.8330	35	270	271.833	-1.8330
13	141	141.25	-0.2500	36	270	141.25	128.7500
14	271	269.5	1.5000	37	271	269.5	1.5000
15	135	141.25	-6.2500	38	146	141.25	4.7500
16	270	269.5	0.5000	39	270	269.5	0.5000
17	270	271.833	-1.8330	40	270	271.833	-1.8330
18	270	271.833	-1.8330	41	271	271.833	-0.8330
19	270	271.833	-1.8330	42	270	271.833	-1.8330
20	268	271.833	-3.8330	43	270	271.833	-1.8330
21	272	271.833	0.1670	44	255	271.833	-16.8330
22	282	271.833	10.1670	45	236	271.833	-35.8330
23	290	271.833	18.1670	46	340	271.833	68.1670

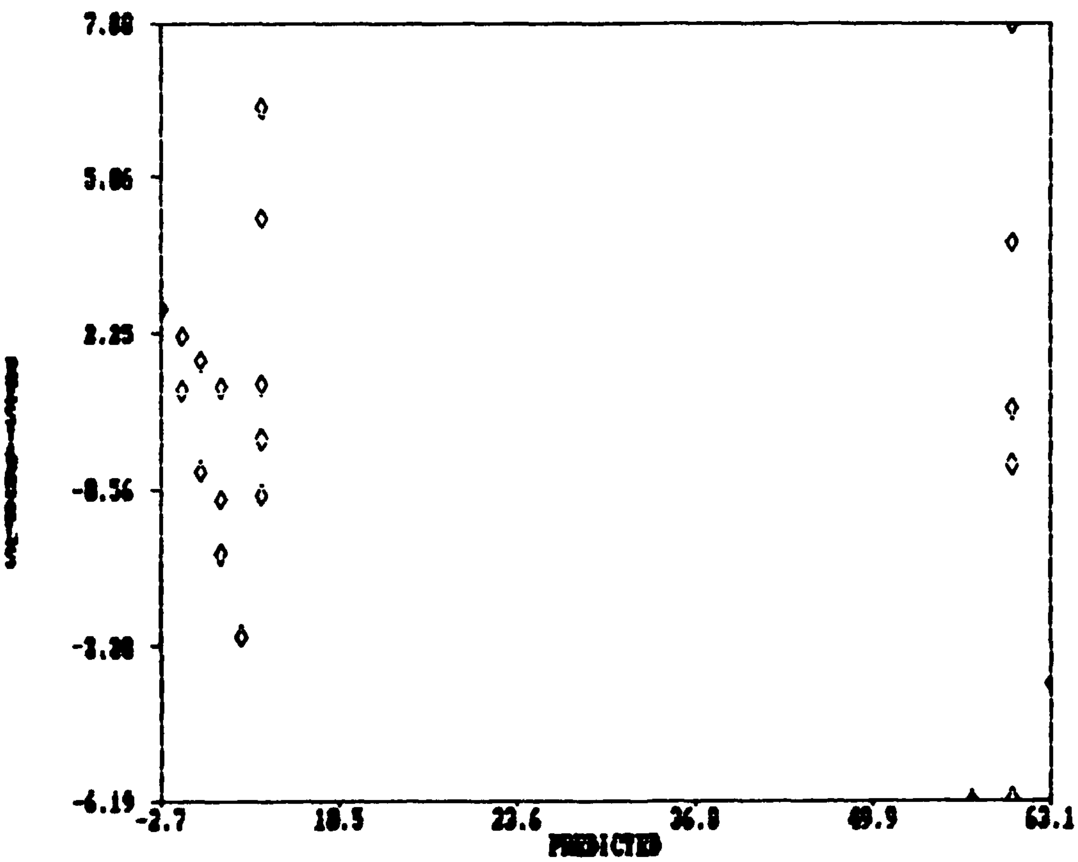
CENTCOM REFUELING RESIDUAL PLOT



Centcom Resupply Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	64	60.125	3.8750	24	4	4.671	-0.6710
2	0	0.25	-0.2500	25	5	4.671	0.3290
3	64	60.125	3.8750	26	0	-1.204	1.2040
4	0	0.25	-0.2500	27	0	-1.204	1.2040
5	5	4.671	0.3290	28	61	60.125	0.8750
6	0	-1.204	1.2040	29	0	0.25	-0.2500
7	11	4.671	6.3290	30	54	60.125	-6.1250
8	0	-1.204	1.2040	31	0	0.25	-0.2500
9	0	1.733	-1.7330	32	9	4.671	4.3290
10	1	1.733	-0.7330	33	1	-1.204	2.2040
11	0	1.733	-1.7330	34	6	4.671	1.3290
12	0	1.733	-1.7330	35	0	-1.204	1.2040
13	59	63.063	-4.0630	36	68	60.125	7.8750
14	0	3.188	-3.1880	37	2	0.25	1.7500
15	51	57.188	-6.1880	38	60	60.125	-0.1250
16	0	-2.687	2.6870	39	0	0.25	-0.2500
17	0	1.733	-1.7330	40	1	1.733	-0.7330
18	0	1.733	-1.7330	41	1	1.733	-0.7330
19	0	1.733	-1.7330	42	0	1.733	-1.7330
20	0	1.733	-1.7330	43	1	1.733	-0.7330
21	1	1.733	-0.7330	44	0	1.733	-1.7330
22	3	1.733	1.2670	45	0	1.733	-1.7330
23	3	1.733	1.2670	46	0	1.733	-1.7330

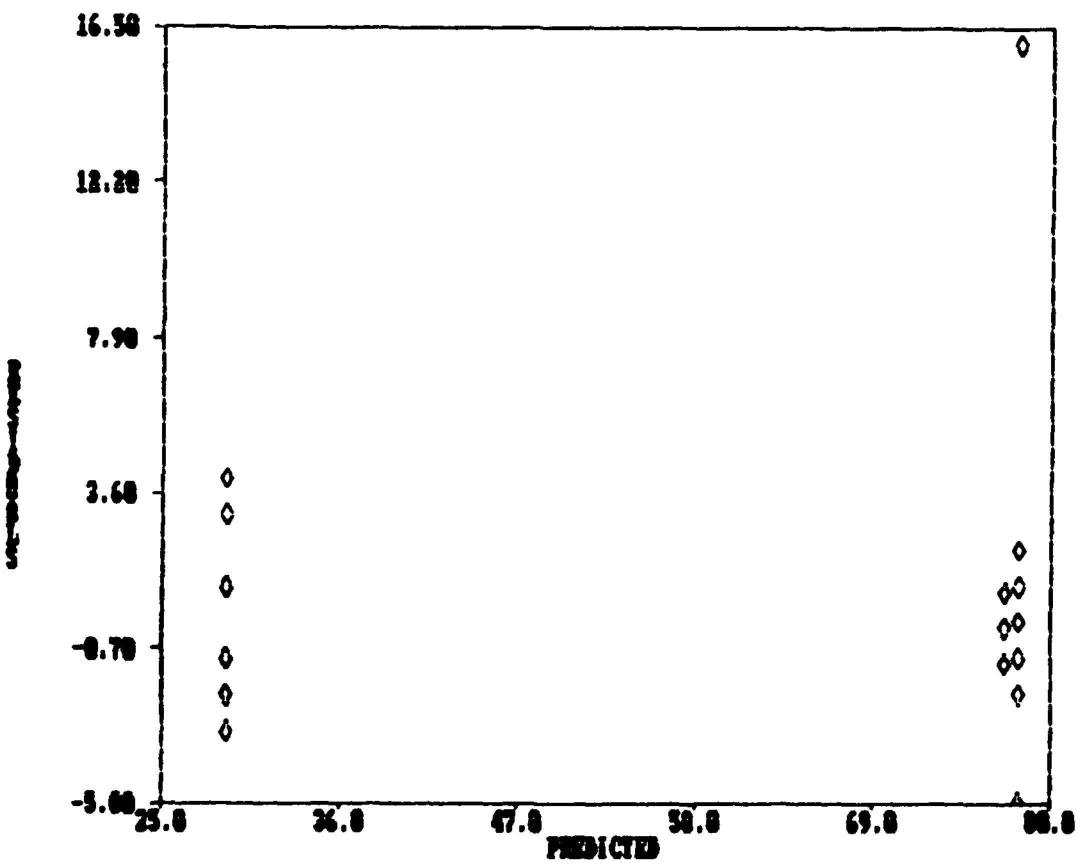
CENTCOM RESUPPLY RESIDUAL PLOT



Centcom Rescue Residuals

RUN	OBSR	PREDICT	RESIDUAL	RUN	OBSR	PREDICT	RESIDUAL
1	26	29	-3.0000	24	78	77.967	0.0330
2	77	77.125	-0.1250	25	80	77.967	2.0330
3	32	29	3.0000	26	77	77.967	-0.9670
4	77	77.125	-0.1250	27	77	77.967	-0.9670
5	77	77.967	-0.9670	28	27	29	-2.0000
6	79	77.967	1.0330	29	78	77.125	0.8750
7	77	77.967	-0.9670	30	30	29	1.0000
8	77	77.967	-0.9670	31	78	77.125	0.8750
9	77	77.967	-0.9670	32	73	77.967	-4.9670
10	77	77.967	-0.9670	33	77	77.967	-0.9670
11	78	77.967	0.0330	34	78	77.967	0.0330
12	78	77.967	0.0330	35	77	77.967	-0.9670
13	28	29	-1.0000	36	26	29	-3.0000
14	77	77.125	-0.1250	37	76	77.125	-1.1250
15	33	29	4.0000	38	30	29	1.0000
16	77	77.125	-0.1250	39	77	77.125	-0.1250
17	78	77.967	0.0330	40	77	77.967	-0.9670
18	77	77.967	-0.9670	41	79	77.967	1.0330
19	80	77.967	2.0330	42	77	77.967	-0.9670
20	77	77.967	-0.9670	43	76	77.967	-1.9670
21	79	77.967	1.0330	44	76	77.967	-1.9670
22	77	77.967	-0.9670	45	79	77.967	1.0330
23	76	77.967	-1.9670	46	94	77.967	16.0330

CENTCOM RESCUE RESIDUAL PLOT



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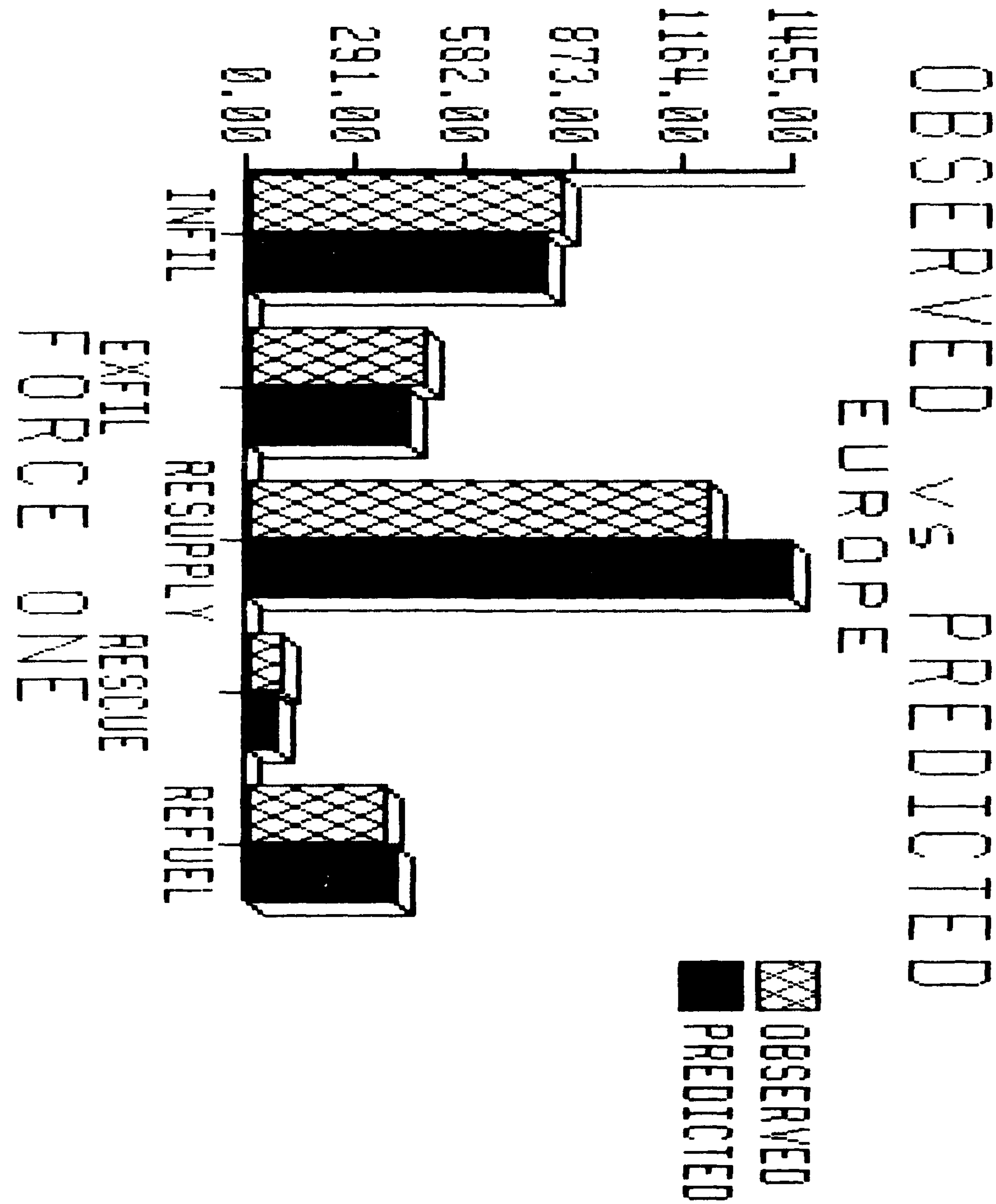
OBSERVED VS PREDICTED
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1164.00
873.00
582.00
291.00
0.00
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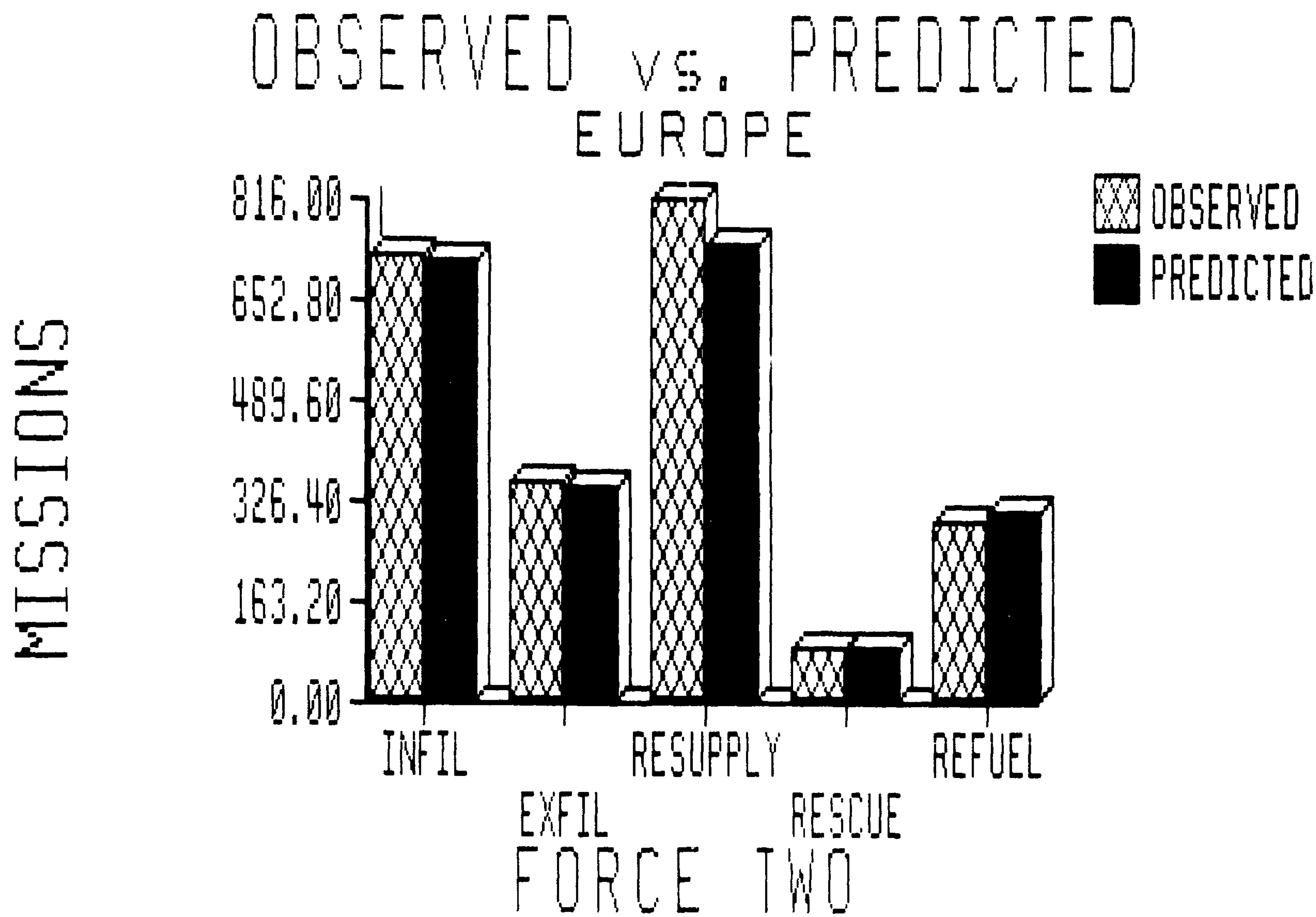
EXFIL
RESUPPLY
RESCUE
REFUEL
FORCE ONE
OBSERVED
PREDICTED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EUROPE
OBSERVED
PREDICTED
MISSIONS
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326.40
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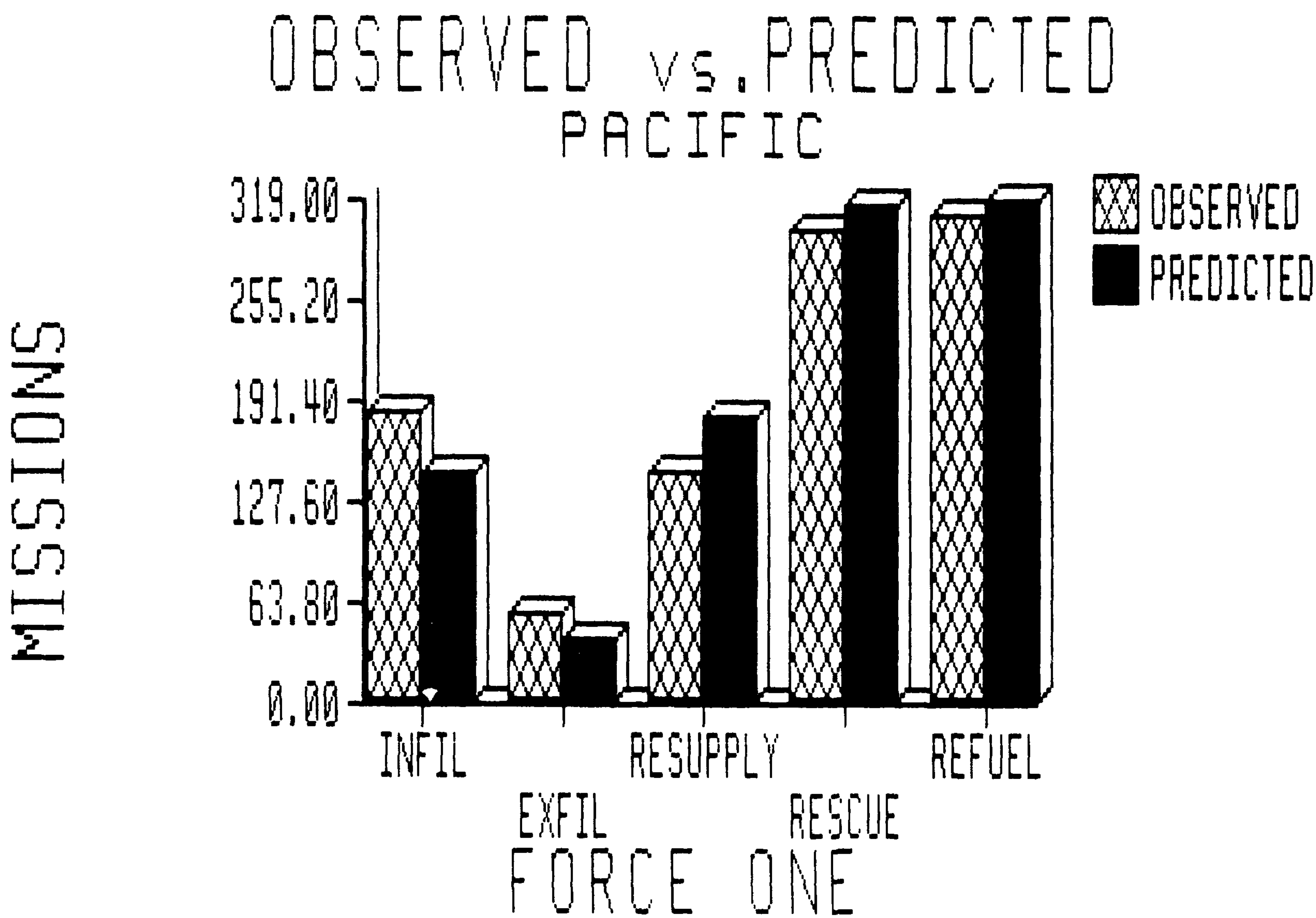
0.00
INFIL
EXFIL
RESUPPLY
RESCUE
REFUEL
FORCE TWO


OBSERVED vs. PREDICTED
PACIFIC
MISSIONS
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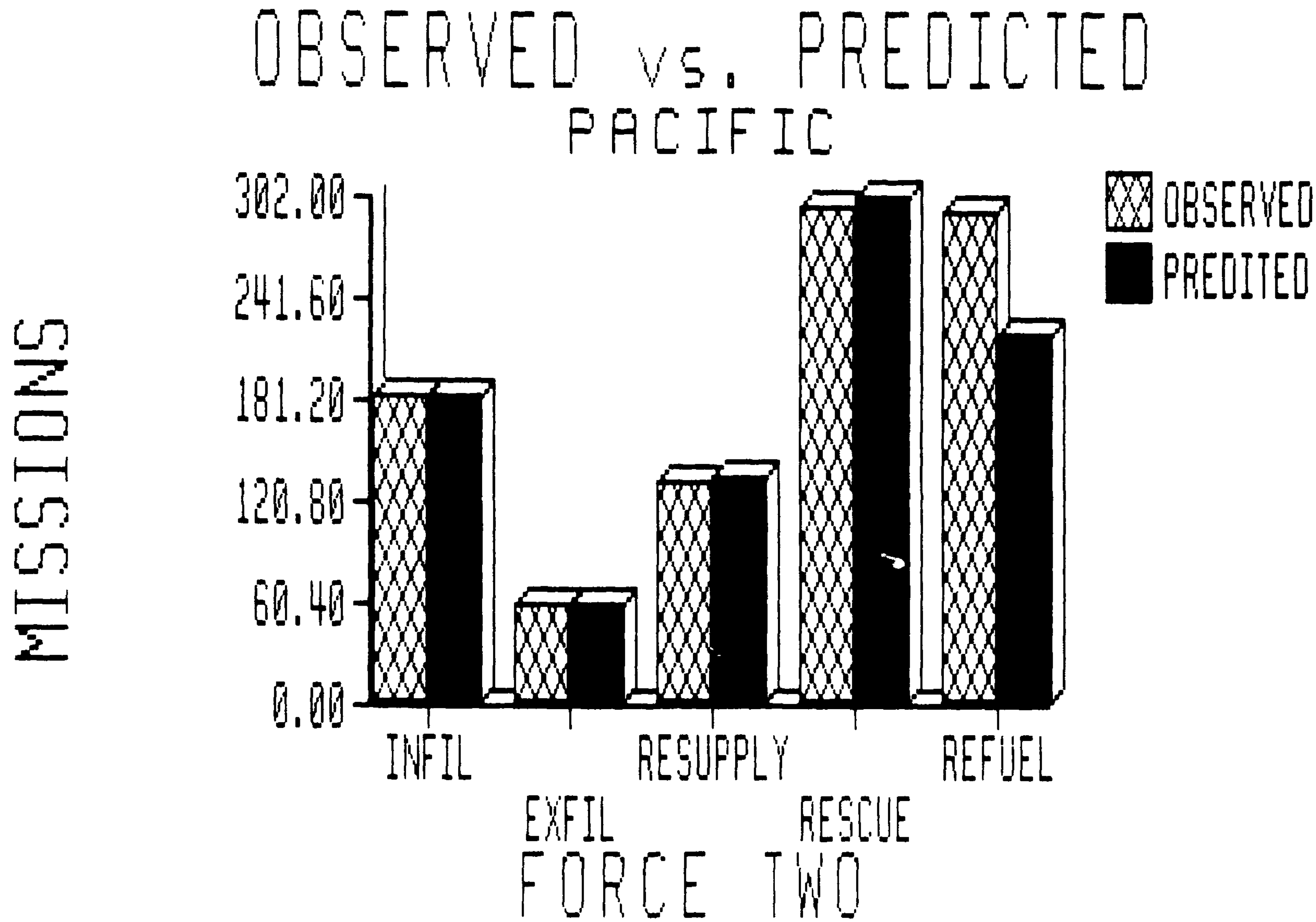
63.80
0.00
INFIL
EXFIL
RESUPPLY
RESCUE
REFUEL
FORCE ONE
OBSERVED
PREDICTED


OBSERVED vs. PREDICTED
PACIFIC
302.00
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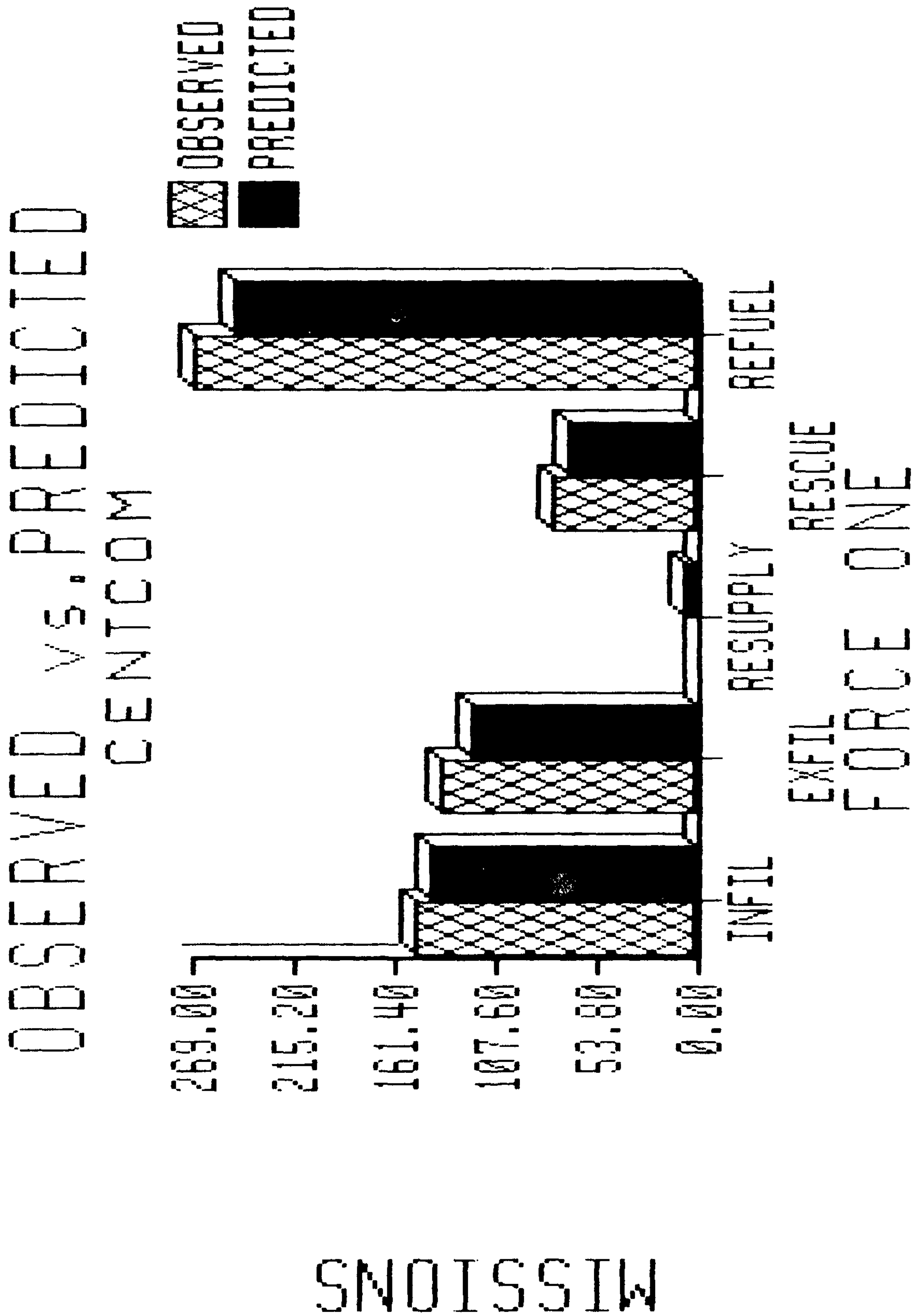
60.40
0.00
MISSIONS
INFIL
EXFIL
RESUPPLY
RESCUE
REFUEL
FORCE TWO
OBSERVED
PREDITED


OBSERVED VS. PREDICTED
CENTCOM
OBSERVED
PREDICTED
MISSIONS
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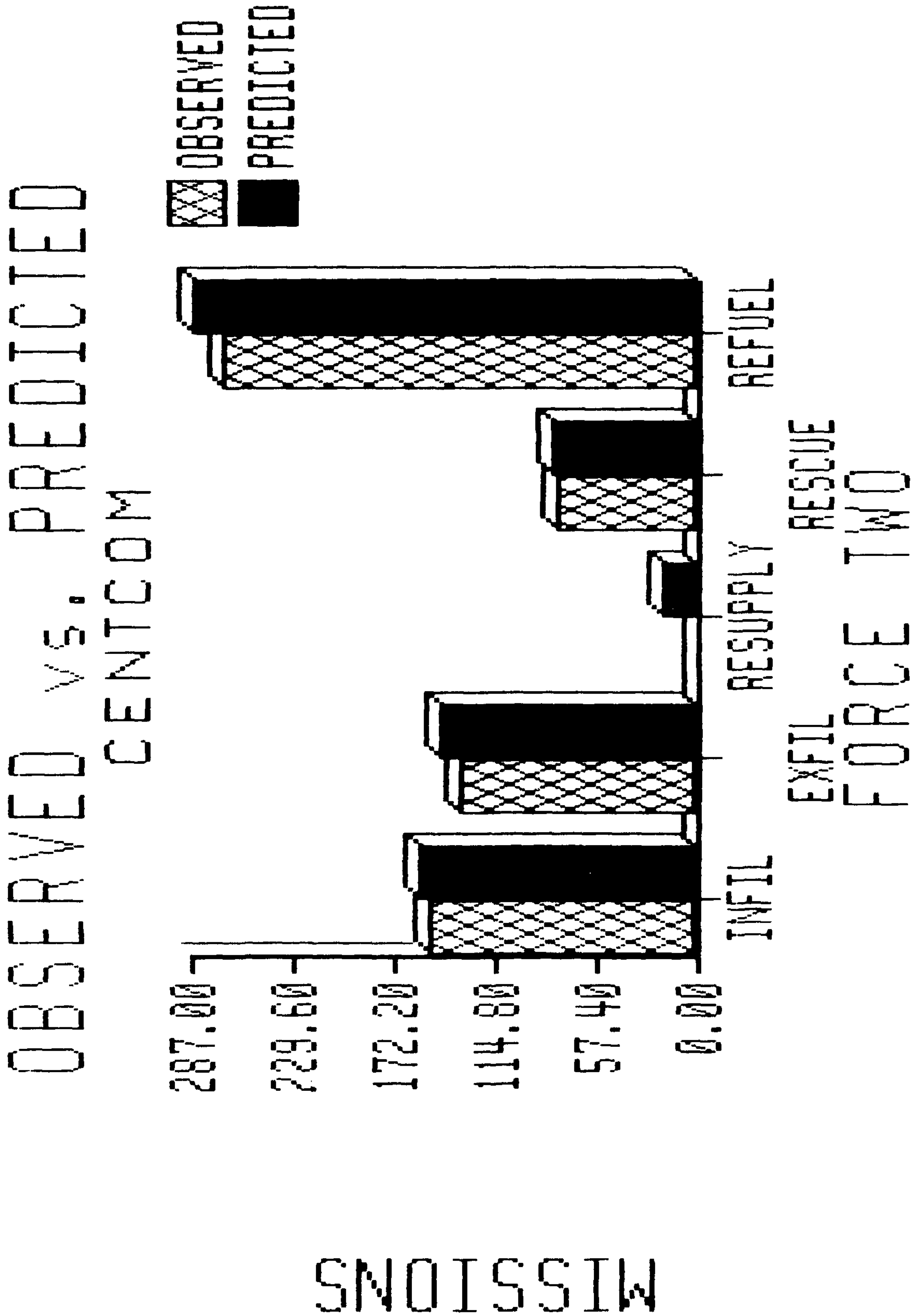
0.00
INFIL
EXFIL
RESUPPLY
RESCUE
REFUEL
FORCE ONE


OBSERVED VS. PREDICTED
CENTCOM
OBSERVED
PREDICTED
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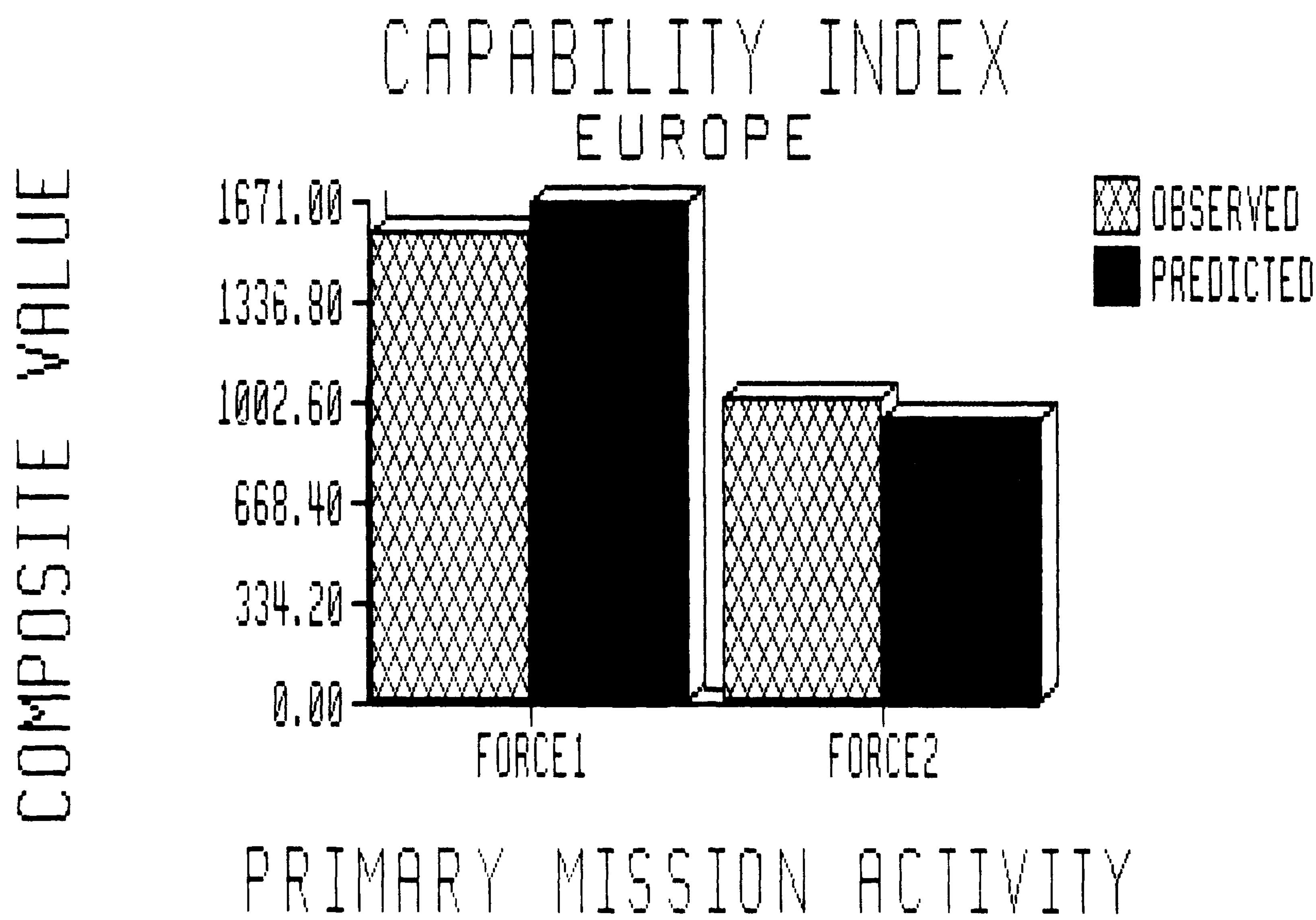
INFIL
EXFIL
RESUPPLY
RESCUE
REFUEL
FORCE TWO
MISSIONS


CAPABILITY INDEX
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OBSERVED
PREDICTED
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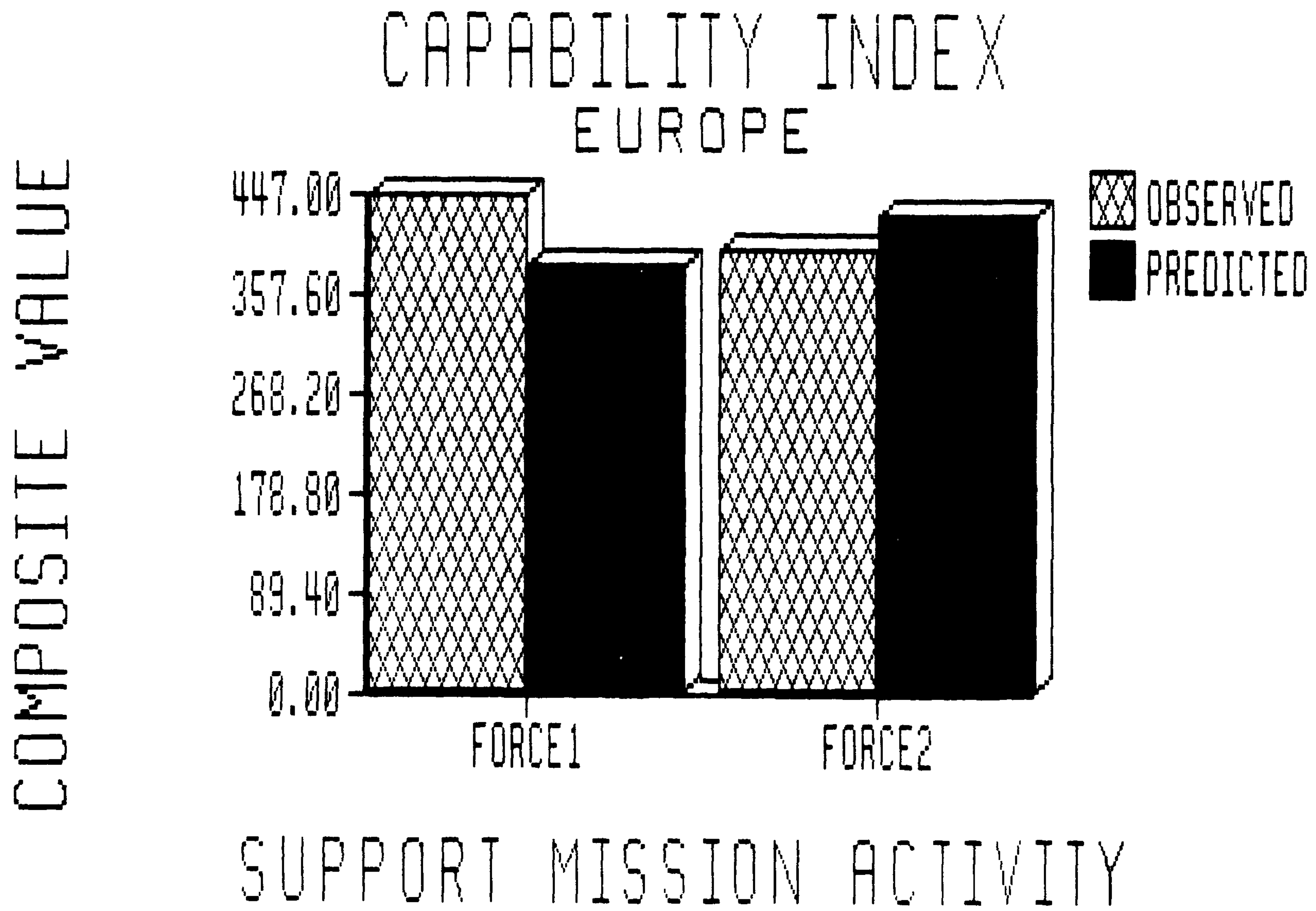
FORCE1
FORCE2
COMPOSITE VALUE
PRIMARY MISSION ACTIVITY



CAPABILITY INDEX
EUROPE
COMPOSITE VALUE
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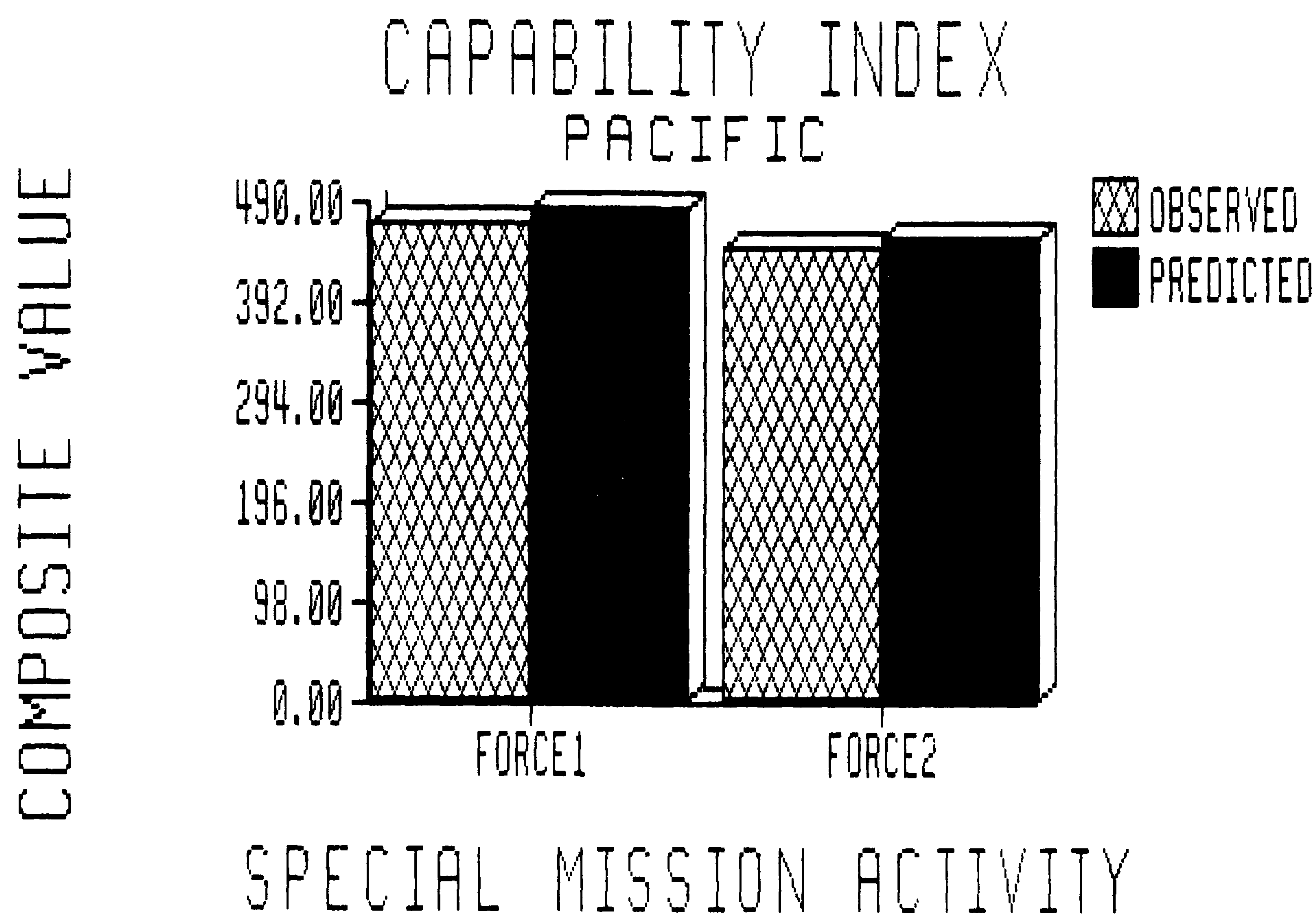
FORCE1
FORCE2
OBSERVED
PREDICTED
SUPPORT MISSION ACTIVITY


CAPABILITY INDEX
PACIFIC
COMPOSITE VALUE
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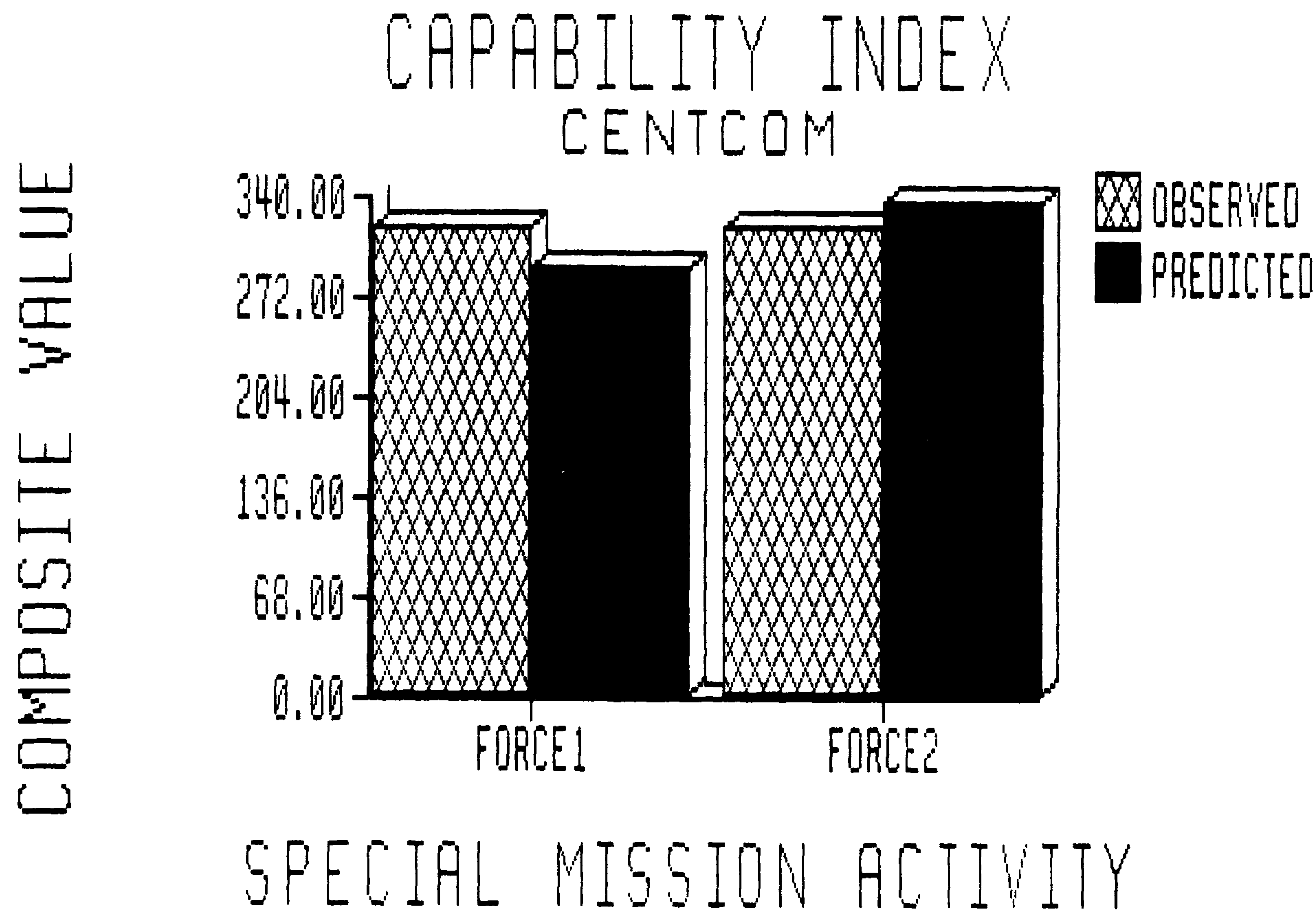
98.00
0.00
FORCE1
FORCE2
OBSERVED
PREDICTED
SPECIAL MISSION ACTIVITY


CAPABILITY INDEX
CENTCOM
COMPOSITE VALUE
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272.00
204.00
136.00
68.00
0.00
FORCE1
FORCE2
OBSERVED
PREDICTED
SPECIAL MISSION ACTIVITY

Vita

Captain Steven Harris [redacted] in 1978 [redacted] entered the USAF as an accounting technician. After a two year commitment he was selected for the Airman Scholarship Commissioning Program at Alabama State University, from which he received the degree of Bachelor of Art in Mathematics in August 1983. He has been assigned to Headquarters Air Force Communication Command and Headquarters Twenty Third Air Force. He then served at Headquarters Military Airlift Command as a combat mobility analyst until entering the School of Engineering, Air Force Institute of Technology, in June 1987.

[redacted]

REPORT DOCUMENTATION PAGE

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12. PERSONAL AUTHOR(S)

Steven Harris, B.A., Capt, USAF

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16. SUPPLEMENTARY NOTATION

17. COSATI CODES			18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)
FIELD	GROUP	SUB-GROUP	

19. ABSTRACT (Continue on reverse if necessary and identify by block number)

Title: A RESPONSE SURFACE APPROACH TO THE COMBAT RESCUE AND SPECIAL OPERATIONS SIMULATION MODEL

Thesis Chairman: Kenneth W. Bauer, JR., Major, USAF
Asst Professor ofOperations Research

This thesis proposes a methodology for producing response surface metamodels to enhance the force sizing capability at Military Airlift Command. Output generated by the Combat Rescue and Special Operations Forces simulation model was used to develop the sets of predictive response equations. The methodology produced statistically accurate predictive metamodels using a Box and Behnken fractional factorial. Multivariate techniques were used to reduce the dimensionality of the

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19. (con't) responses modeled by the simulation model to further enhance the decision making process on force sizing issues.